# Essays on Currency Risks and Returns

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**Abstract**

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**Chapter 1**[1] proposes using foreign exchange rate currency options with different strike prices and maturities to capture both currency risks and expectations, for helping understand currency return dynamics. We show that currency returns, which are notoriously difficult to model empirically, are well-explained by the term structures of forward premia and options-based measures of FX expectations and risk. Although this finding is to be expected, expectations and risk have been largely ignored in empirical exchange-rate modeling. Using daily options data for six major currency pairs, we first show that currency options-implied standard deviation, skewness, and kurtosis consistently improve the explanatory power of

[1] This chapter is based on a work co-authored with Yu-Chin Chen and Ranganai Gwati.

quarterly currency returns than a standardized UIP regression. We then show that adding term structure information of options-implied moments further improves the explanatory power. Our results highlight the importance of expectations and risk in explaining currency returns and suggest that this information may be particularly useful during a crisis period.

**Chapter 2** studies the term structure of currency risk using FX options data, and finds it able to explain the cross-sectional variation of currency excess returns. With the tool of a new FX risk index, "FCX", I look into currency risk term structure and measure its shape by level and slope. I consistently find that for currencies paired by US dollars, the term structure of currency risk is flat at a low level prior to the 2008 crisis, upward-sloping after the crisis and peaks at a high level with a prominently negative slope during the crisis. This work is believed to be new in the currency research field. I then use this information to build trading strategies, earning a profit by longing currencies with the highest level or slope and shorting ones with the lowest level or slope. The profit by sorting slope is significantly high and robust to the 2008 crisis period, with a low correlation to the Carry Trade return, suggesting extra information in risk than the interest rate. Next, I extract global risk factors by level and slope to help understand the currency excess return, a long-lasting puzzle. The global risk factor by level substantially improves the cross-sectional explanatory power in currency excess returns compared to Lustig et al. (2011). Furthermore, I show that there is certain high risk corresponding to a high level and low slope, and high interest rate currency earns returns co-varying negatively to this risk, implying that it is a risky asset and thus requires a high risk premium, which explains the Carry Trade return well.

**Chapter 3**[2] explores the possible macroeconomic connection in currency markets through the channel of FX risk term structure. There is a consensus in the literature that exchange rates are empirically "disconnected" from fundamentals, but a possible theoretical insight is that macroeconomic volatility shocks induce time-varying risks in the exchange rates. This chapter empirically investigates the connection between macroeconomic fundamentals and time-varying currency risks captured by the FX risk term structure, following the main findings of chapters 1 and 2. This chapter use both a small dataset of directly observable, country-specific key macroeconomic and international variables implied by exchange rate structural modeling and a small number of macroeconomic factors constructed from a large dataset of 126 U.S. macroeconomic series by principal component analysis. We perform a VAR analysis to examine impulse responses of FX risk term structure to the shocks of macroeconomic events and find that production variables can generate a relatively consistent and systematic impact pattern, which suggests potential macroeconomic connection. We also perform a direct single regression, regressing the 126 macroeconomic series of eight different groups on the FX risk term structure and apply the group LASSO technique for variable selection. Variables among both macroeconomic fundamentals and financial series are commonly selected, which suggests that financial markets' co-movements also exist besides potential macroeconomic connection.

[2] This chapter is based on a work co-authored with Yu-Chin Chen and Yida Li.

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# DEDICATION

To my mom Chunrong Li and my husband Hongbin Liu.

# Chapter 1. CURRENCY RETURNS AND THE TERM STRUCTURE OF FX DERIVATIVES

Yu-Chin Chen, Ranganai Gwati, Jingyi Ren

## 1.1 INTRODUCTION

The exchange rate economics literature has faced many empirical puzzles over the years. For example, although theory predicts that nominal exchange rates should depend on current and expected future macroeconomic fundamentals, the consensus in the literature is that exchange rates are essentially empirically “disconnected” from the macroeconomic variables that are supposed to determine them. This empirical disconnect comes in the form of low correlations between nominal exchange rates and their supposed macro-based determinants and in the form of poor performance of macro-based exchange rate models in out-of-sample forecasting.[3]

A related empirical anomaly that has received considerable attention in the literature is the uncovered interest parity (UIP) or forward premium puzzle. The UIP puzzle is the empirical irregularity showing that the forward exchange rate is a biased predictor of future spot exchange rates. The UIP puzzle is taken seriously in the exchange rate literature because the UIP condition is a property of most open-economy macroeconomic models.

One manifestation of this empirical irregularity is that countries with higher interest rates tend to see their currencies subsequently appreciate, and a "carry-trade" strategy, exploiting this pattern,

[3] See Engel (2014) for a review.

on average, delivers excess currency returns.[4] This violation of the UIP condition is commonly attributed to time-varying risk premia and biases in (measured) market expectations. However, empirical proxies based on surveyed forecasts or standard measures of risk - for instance, ones built from consumption growth, stock market returns, or the Fama and French (1993) factors -have been unsuccessful in explaining the puzzle.[5] As such, while recognizing the presence of risk, macroeconomic-based approaches to modeling exchange rates often ignore risk in empirical testing.[6][7]

This paper argues that the persistent empirical puzzles faced by the exchange rate economics literature are most likely due to overly restrictive preferences and distributional assumptions in conventional testing methods. For example, researchers typically assume that exchange rate returns are normally distributed or that investors' utility functions depend only on the mean and variance. We argue that these auxiliary assumptions often inadequately account for either the forward-looking property of nominal exchange rates or potential skewness and/or fat tails in the distribution of currency returns.

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[4] A carry trade strategy is to borrow low-interest currencies and lend in high-interest currencies or to sell forward currencies that are at a premium and buy forward currencies with a forward discount. I will talk more about carry trade in my chapter 2.

[5] See Engel (1996) for a survey of the forward premium literature as well as recent studies such as Burnside et al. (2010) and Bacchetta et al. (2009).

[6] See, for instance, Engel and West (2005), Mark (1995).

[7] On the finance side, efforts aiming to identify portfolio return-based "risk factors" offer some empirical success in explaining the cross-sectional distribution of excess FX returns but have little to say about bilateral exchange rate dynamics (see, for example, Lustig et al. (2011); Verdelhan (2018)). Lustig et al. (2011) and Verdelhan (2018) identify a "carry factor" and a "dollar factor" based on cross sections of interest rate-sorted currency returns. I will talk more about these risk factors in my chapter 2.

We empirically demonstrate that currency risks, as captured by higher order moments of perceived currency returns distributions and expectations, captured by the term structure of FX option prices, do matter in explaining exchange rate movements. We highlight the usefulness of capturing risks and expectations, by showing that quarterly exchange rate movements are well explained by the term structure of the first through fourth moments of options-implied returns distributions, with the adjusted R-squared ranging from 54% for USDJPY to 70% for NZDUSD. This high explanatory power is robust to different time periods, while the coefficients of the variables tend to be time-varying.

Simple derivatives such as forwards and futures have been used extensively in explaining exchange rate movements.[8] Payoffs from forward contracts, however, are linear in the return on the underlying currency and as such do not contain as useful a set of information as the non-linear contracts we examine. Conceptually, since payoffs of option contracts depend on the uncertain future realization of the price of the underlying asset, option prices must reflect market sentiments and beliefs about the probability of future payoffs.

Our use of FX options price data and related empirical methodologies has a number of motivating factors. First, options are forward-looking by construction, which means option prices should, therefore, be able to incorporate information such as forthcoming regime switches or the presence of a peso problem.[9] Second, option prices are deeply rooted in market participant behavior because they are based on what market participants do instead of what they say. Furthermore, cross sections

[8] See, for example, Hansen and Hodrick (1980) and Clarida and Taylor (1997) among many others.
[9] The peso problem refers to the effects on inferences caused by low-probability events that do not occur in the sample, which can lead to a positive excess return.

of option prices imply a subjective probability distribution of future spot exchange rates, which captures both market participants' beliefs and preferences.[10] Third, modern techniques such as the Vanna-Volga method[11] and the methodology of Bakshi et al. (2003) facilitates elegant and model-free computation of options-implied higher order moments of future exchange rate changes.

## 1.2 Why Higher Order Moments and Term Structure

The first purpose of this section is to emphasize the role that failure to adequately capture market expectations and perceived risk in the FX market potentially plays in causing both the UIP puzzle and the macro disconnect puzzle. The second purpose is to argue that the term structure of option-implied higher order moments captures both perceived risk and expectations of future macroeconomic conditions. Lastly, we argue that option prices potentially offer cleaner proxies of FX global risk, which can be useful to the recent strand of literature emphasizing the role of global risk in explaining cross-sections of both currency excess returns and currency returns.

### 1.2.1 *Forward Premium Puzzle and Excess Currency Returns*

The efficient market condition for the foreign exchange markets, under rational expectations, equates cross border interest differentials $i_t - i_t^*$ with the expected rate of home currency depreciation, adjusted for the risk premium associated with currency holdings, $\rho_t$:[12]

[10] This distribution is commonly referred to as the "risk-neutral distribution" though it does NOT imply that the distribution is derived under risk-neutrality. On the contrary, it incorporates both the expected physical probability distribution of future exchange rate realization as well as the risk premium or compensation required to bear the uncertainty.

[11] See Castagna and Mercurio (2007).

[12] In this paper, we define the exchange rate as the domestic price of foreign currency. The superscript * indicates a foreign-country variable. A rise in the exchange rate indicates a depreciation of the home currency. However, "home" does not have a geographical significance but follows the FX market conventions. See table (1.1A).

$$E_t \Delta s_{t+\tau} = i_t^{\tau} - i_t^{\tau,*} + \rho_{t+\tau}. \quad (1.1)$$

This condition is expected to hold for all investment horizons $\tau$ with interest rates that are at matched maturities. Ignoring the risk premium term, numerous papers have tested this equation since Fama (1984) and found systematical violations of this UIP condition:

$$s_{t+\tau} - s_t = \alpha + \beta\left(i_t^{t+\tau} - i_t^{t+\tau,*}\right) + \varepsilon_{t+\tau};\ E_t\varepsilon_{t+\tau} = 0, \forall t,$$

$$H_0\colon \beta = 1 \quad (1.2)$$

with an estimated $\beta < 0$ and R-squared that is usually close to zero. This is the so-called uncovered interest rate parity puzzle or the forward premium puzzle (see Engel (1996) for a survey of the literature). To see the connection with forward rates, we note that the covered interest parity condition, an empirically valid no-arbitrage condition, equates the forward premium $f_t^{t+\tau} - s_t$ with interest differentials. The risk-neutral UIP condition above thus implies that the forward rate should be an unbiased predictor for future spot rate: $E_t s_{t+\tau} = f_t^{t+\tau}$ or $s_{t+\tau} = f_t^{t+\tau} + u_{t+\tau}$, where $E_t u_{t+\tau} = 0, \forall t$.

We should next define FX excess returns as the rate of return across borders net of currency movement, and one can see that the UIP or forward premium puzzle can be expressed as a non-zero averaged excess return over time:

$$xr_{t+\tau} = f_t^{t+\tau} - s_{t+\tau} = \left(i_t^{t+\tau} - i_t^{t+\tau,*}\right) - \Delta s_{t+\tau} = \rho_{t+\tau} + u_{t+\tau}. \quad (1.3)$$

It is natural then to note that the empirical failure of the risk-neutral UIP condition can be attributable to either the presence of a time-varying risk premium $\rho_{t+\tau}$ or that expectation error $u_{t+\tau}$ may not be i.i.d. with mean zero over time. If the distribution of either of these is not mean zero over the time series, empirical estimates of the slope coefficient in regression equation (1.2) would likely suffer an omitted variable bias or other complications.

### 1.2.2 *Why Derivatives Options and Implied Higher Order Moments?*

(1) Why derivatives options

Breeden and Litzenberger (1978) show that in complete markets, the call option pricing function $C$ and the exercise price $K$ are related as follows:

$$\frac{\partial^2 C}{\partial K^2} = e^{-r^d \tau} \pi_t^Q (S_{t+\tau}), \qquad (1.4)$$

where $r^d$ and $r^f$ are the domestic and foreign risk-free interest rates, respectively, and $\pi_t^Q (S_{t+\tau})$ is the risk-neutral probability density function (pdf) of future spot rates. Equation (1.4) implies that, in principle, we can estimate the whole pdf of time $S_{t+\tau}$ spot exchange rate from time $t$ volatility smile. Once the distribution is available, it becomes possible to get empirical estimates of the standard deviation, skewness, kurtosis and even higher order moments of the market perceived probability density of $S_{t+\tau}$ given information available at time $t$.

In addition to the Breeden and Litzenberger (1978) result in equation (1.4), we note that although market participants can be treated as if they are risk-neutral for the purpose of option-pricing, option prices theoretically contain information about both investor beliefs and risk preferences, as shown from the following formula for the price of a European-style call option:

$$C(t,K,\tau) = \int_K^\infty M_{t,t+\tau}(S_{t+\tau} - K)\pi_t^P(S_{t+\tau})dS_{t+\tau} = e^{-r^d\tau}\int_K^\infty (S_{t+\tau} - K)\pi_t^Q(S_{t+\tau})dS_{t+\tau}. \quad (1.5)$$

In equation (1.5), $M_{t,t+\tau}$ is the pricing kernel, which captures the investor's degree of risk aversion, and $\pi_t^P(S_{t+\tau})$ is the physical probability density function of future spot exchange rates.[13]

A forward contract can, in fact, be viewed as a European-style call option with a strike price of zero. To see this, we recall that the theoretical forward exchange rate is given by the formula below, which equals equation (1.5) at $K = 0$.

$$F_{t,t+\tau} = e^{-r^d\tau}\int_0^\infty S_{t+\tau}\pi_t^Q(S_{t+\tau})dS_{t+\tau} = C(t,0,\tau). \quad (1.6)$$

The relationship between options and forwards in equation (1.6) suggests that the cross section of option prices should, at a minimum, contain as much information about investor beliefs and preferences as that contained in forward prices.

(2) Why higher order moments?

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[13] In the second expression, the pricing kernel $M_{t,t+\tau}$ is performing both the risk-adjustment and discounting functions, while in the third expression, these functions are divided between $\pi_t^Q$ and $e^{-r^d\tau}$.

We start with the problem of an investor who, in each period, allocates her portfolio among risky assets with the goal of maximizing the expected utility of next period wealth $W_{t+1}$. In each period, the investor has $n$ risky assets to choose from. Let us further assume that the investor has CARA utility and that returns are conditionally normally distributed. The CARA utility assumption means the utility is given by $U(W_{t+1}) = -e^{-\gamma W_{t+1}}$, where $\gamma \geq 0$ is the coefficient of absolute risk aversion. In addition to risk neutrality and rational expectations assumptions, the UIP condition also hinges on the rather restrictive auxiliary assumptions that FX returns are i.i.d. normal over time and that investors have constant absolute risk aversion (CARA) utility. The two additional assumptions have the effect of reducing the representative investor's optimal asset allocation problem to a mean-variance optimization problem.

However, if the distribution of portfolio returns is asymmetric, the investor's utility function is of a higher order than quadratic, or the mean and variance do not completely determine the distribution of asset returns, then higher order moments and their signs must be taken into account in the portfolio asset allocation problem. In this subsection, we present a framework for incorporating higher order moments into the asset allocation problem. Jondeau et al. (2007) consider a Taylor series expansion of the utility function around the expected utility up to the fourth order and taking the conditional expectation yields[14]

$$E_t[U(W_{t+1})] \approx e^{-\gamma \mu_p} \left[1 + \frac{\gamma^2}{2}\sigma_p^2 - \frac{\gamma^3}{6}s_p^3 + \frac{\gamma^4}{24}k_p^4\right], \qquad (1.7)$$

[14] Please refer to Chen and Gwati (2013) for details.

where $\sigma_p^2$, $s_p^3$ and $k_p^4$ are the volatility, skewness and kurtosis of portfolio return. It is clear from equation (1.7) that under CARA utility, investors prefer positive skewness and dislike high variance and kurtosis. For CARA utility, the weight the investor puts on the higher order moments depends on the degree of the risk aversion parameter $\gamma$. In more general settings, however, the weight on the $n^{th}$ moment depends on the $n^{th}$ derivative of the utility function, and the signs of sensitivities of the utility function to changes in higher moments cannot be easily pinned down. If the moments are not orthogonal to each other, then the effect on the utility of increasing one moment might not be straightforward. Scott and Horvath (1980) establish some general conditions for investor preference for skewness and kurtosis.

From above we propose our first hypothesis: Besides forward rate and volatility, higher order moments can also help explain currency returns, and thus, we introduce our first main regression (1.8):

$$s_{t+\tau}^{i} - s_{t}^{i} = \alpha + \beta_1\left(f_t^{i,t+\tau} - s_t^{i}\right) + \beta_2 stdev_t^{i,t+\tau} + \beta_3 skew_t^{i,t+\tau} + \beta_4 kurt_t^{i,t+\tau} + \varepsilon_{t+\tau}^{i}. \quad (1.8)$$

### 1.2.3 *Why Term Structure of Option-Implied Moments?*

Rearranging the UIP relationship in equation (1.1) and iterating forward, we can show that the nominal exchange rate depends on current and expected future interest rate differentials as well as on expected future risk:[15]

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[15] The term $\lim_{j\to\infty}\left(E_t s_{t+j}\right)$ can be interpreted as the long-run exchange rate, which is not in the scope of the paper.

$$s_t = -\sum_{j=0}^{\infty} E_t\left(i_{t+j} - i_{t+j}^*\right) - \sum_{j=0}^{\infty} E_t \rho_{t+j} + \lim_{j \to \infty}\left(E_t s_{t+j}\right). \quad (1.9)$$

Expression (1.9) highlights the link between the exchange rate and macroeconomic fundamentals. There is a huge amount of literature linking the term structure of interest rates (yield curve) to the expected future dynamics of macroeconomic fundamentals such as monetary policy, inflation, and output by observing that short term interest rates are monetary policy variables that depend on macroeconomic variables such as inflation and output while longer-term yields are risk-adjusted averages of expected future short rates.[16] Chen and Tsang (2013) extend this strand of literature to the open economy context by noting that the term structure of interest rate differentials (relative yield curve) contain information about the expected future dynamics of differences in macroeconomic fundamentals. We note that the relative yield curve captures the same information about expected macroeconomic fundamentals as the term structure of option-implied first moments of future exchange rate movements. We extend the literature on yield curve-exchange rate linkage by investigating the ability of entire option-implied distributions to explain exchange rate dynamics.

Writing the exchange rate in the form of equation (1.9) also demonstrates the importance of capturing expectations and risk in the empirical modeling of exchange rates. Standard empirical approaches usually impose distributional assumptions that reduce the sum of expected future fundamentals to equal current fundamentals and ignore risk.[17]

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[16] See Diebold et al. (2005) for a survey.
[17] See Engel and West (2005), Mark (1995).

There is also a strand of literature that documents the empirical success of empirical exchange rate models that capture information in the term structure of forward premia. Clarida and Taylor (1997) and Clarida et al. (2003) show that even if the forward rate is a biased predictor of the future spot rate (the forward premium puzzles), the term structure of forward premia still contains information useful for predicting subsequent exchange rate changes. This line of literature is linked to Chen and Tsang (2013) by observing that through the empirically valid covered interest parity (CIP) condition, the forward premium equals the interest rate differential at all maturities.

From above, we propose our second hypothesis: Besides the forward rate, volatility, and higher-order moments at a matched maturity, their values across different maturities, i.e. term structure, can also help explain currency returns, and thus we introduce our second main regression (1.10), where $M$ represents the number of maturities:

$$s_{t+\tau}^{i} - s_{t}^{i} = \alpha + \sum_{j=0}^{M} \beta_{1,j}\left(f_{t}^{i,t+j} - s_{t}^{i}\right) + \sum_{j=0}^{M} \beta_{2,j} stdev_{t}^{i,t+\mathrm{j}} + \sum_{j=0}^{M} \beta_{3,j} skew_{t}^{i,t+j} + \sum_{j=0}^{M} \beta_{4,j} Kurt_{t}^{i,t+j} + \varepsilon_{t+\tau}^{i}. \quad (1.10)$$

## 1.3 DATA AND BEHAVIOR

Our options data consists of daily over the counter (o-t-c) option prices for the six currency pairs listed in table (1.1) and covering the period 1st January 1998 to 23rd October 2014 from JP

Morgan. The spot rates, forward rates, and risk-free interest rates are obtained from the Federal Reserve Bank of St. Louis.

**Table 1.1**

We use the methodology of Bakshi et al. (2003) (henceforth, BKM) to extract model-free option-implied standard deviation, skewness, and kurtosis from the volatility smile. Grad (2010) and Jurek (2014) also use the BKM methodology to extract FX options-implied higher order moments.[18]

The extracted risk-neutral moments of $log\frac{S_{t+\tau}}{S_t}$ are very persistent, with AR(1) coefficients as high as 0.99. Zivot and Andrews (2002) unit root tests, however, suggest that almost all the implied moments are stationary with structural breaks in the means around early 2001, late 2008, and early 2010. There are also some outliers in some of the skewness and kurtosis series, especially for maturities of nine and 12 months. In general, the level of these moments, as well as their volatility and persistence, all increase in magnitude as maturity increases. Table (1.2) records the summary statistics of these implied moments.

**Table 1.2**

The skewness on average inclines negatively but shows different signs by different time periods, as shown in figure (1.1). For example, the skewness of AUDUSD remains negative from 2004 to

[18] Please refer to Chen and Gwati (2013) for detailed BKM steps.

2008, indicating that the Australian dollars depreciates, and USDJPY is negative, which is consistent with the carry-trade period but starts to increase after 2008 and turns positive after 2012.

When we look at all these implied moments of different horizons together, the time series shape is informative about the timing of the financial crisis. As shown in figure (1.1), the behavior of all maturities' volatility together is very different during the 2008 crisis. For skewness and kurtosis, they can signal both the 2001 crisis and 2008 crisis, even with the predictive power that they behave differently around one year before the crisis period, which is consistent with public discussion. For USDJPY, the skewness and kurtosis of different horizons can signal Abenomics in 2012 as well.

To better illustrate the horizon information of these moments, figure (1.2) plots the term structure of moments on representative days. The volatility term structure tends to be upward sloping with prominently higher levels during the 2008 crisis. The skewness term structure tends to be downward sloping, with a prominently steeper slope around one year before the 2001 and 2008 crises, respectively. The kurtosis term structure tends to be upward sloping with a prominently steeper slope around one year before the 2001 and 2008 crises, respectively. For USDJPY, skewness and kurtosis term structure have a steeper slope around Abenomics in 2012 as well.

**Figure 1.1**

**Figure 1.2**

## 1.4 EMPIRICAL STRATEGY AND MAIN RESULTS

### 1.4.1 *Can the Term Structure of Implied Moments Predict Currency Returns?*

For each currency pair $i$, we start by estimating the standard UIP regression, and we look at quarterly currency returns where $\tau = 3m$ to align with the frequency of macro events. In addition, as suggested by section 1.3 about the presence of structural breaks in both options information and currency returns, we use Bai and Perron's (2003) structural break test to identify three break dates, as shown in table (1.3). We add these structural break indicator variables into the regression, forming our UIP regression equation (1.11), where $D1^i$, $D2^i$, $D3^i$ are zero before the break date and equal to one otherwise. We focus on model fit and joint significance rather than testing whether the $\beta$ coefficient is equal to 1. As shown in column A of table (1.3), for all currency pairs, the forward premia coefficients are statistically significant at the 1% level and the adjusted R-squared ranges from 14% to 26%.

$$s_{t+3m}^i - s_t^i = \alpha^i + \beta_{1,2,3}^i\left(D1^i + D2^i + D3^i\right) + \beta_4^i\left(f_t^{i,t+3m} - s_t^i\right) + \beta_{5,6,7}^i\left(D1^i + D2^i + D3^i\right)\left(f_t^{i,t+3m} - s_t^i\right) + \varepsilon_{t+3m}^i. \quad (1.11)$$

We then consider the predictive ability of matched frequency option-implied higher moments, that is, the first to fourth moments of the distribution of $log\,\frac{S_{t+3m}}{S_t}$. Similarly, we add three structural break indicator variables into the regression, forming our high moment regression equation (1.12). As shown in column B of table (1.3), the adjusted R-squared for the matched-frequency high moment regressions ranges from 43% to 55%, which is consistently higher than that of the standard

UIP. In addition, coefficients on the higher order moments are always jointly significant at the 1% level.

$$
\begin{aligned}
s_{t+3m}^{i} - s_{t}^{i} = \alpha^{i} + \beta_{1,2,3}^{i}\left(D1^{i} + D2^{i} + D3^{i}\right) \\
+ \left[\beta_{4}^{i}\left(f_{t}^{i,t+3m} - s_{t}^{i}\right) + \beta_{5}^{i} stdev_{t}^{i,t+3m} + \beta_{6}^{i} skew_{t}^{i,t+3m} + \beta_{7}^{i} kurt_{t}^{i,t+3m}\right] \\
+ \beta_{8,\dots,19}^{i}\left(D1^{i} + D2^{i} + D3^{i}\right)\left[\left(f_{t}^{i,t+3m} - s_{t}^{i}\right) + stdev_{t}^{i,t+3m} + skew_{t}^{i,t+3m} \right. \\
\left. + kurt_{t}^{i,t+3m}\right] + \varepsilon_{t+3m}^{i}. \quad (1.12)
\end{aligned}
$$

Lastly, we move on to studying whether the term structure of options-implied moments has predictive ability for subsequent currency returns. That is, we consider the first to fourth moments of all maturities ranging from one week to 12 months. In addition, we relate the term structure of the first moment to a relative yield curve (Chen and Tsang, 2013), that is, interest rates of two countries across all maturities ranging from three to 120 months. Since this is a large set of regressors, we reduce its dimension by extracting six principal components from those variables, denoted by $PC_p$, accounting for more than 90% variance among them. Then, we add three structural break indicator variables into the regression, forming our term structure regression equation (1.13). As shown in column C of table (1.3), the adjusted R-squared for the term structure regressions ranges from 54% to 70%, which is consistently higher than that of the standard UIP and even higher than that of the high moment regressions.

$$s_{t+3m}^{i} - s_{t}^{i} = \alpha^{i} + \beta_{1,2,3}^{i}\left(D1^{i} + D2^{i} + D3^{i}\right)$$

$$+ \beta_{4,\dots,9}^{i} \sum_{p=1}^{6} PC_{p}^{i} \left[ \sum_{j=3m}^{120m} i_{t}^{i,t+j} + \sum_{j=3m}^{120m} i_{t}^{US,t+j} + \sum_{j=1wk}^{12m} stdev_{t}^{i,t+\mathrm{j}} + \sum_{j=1wk}^{12m} skew_{t}^{i,t+j} + \sum_{j=1wk}^{12m} Kurt_{t}^{i,t+j} \right]$$

$$+ \beta_{10,\dots,27}^{i}\left(D1^{i} + D2^{i} + D3^{i}\right) \sum_{p=1}^{6} PC_{p}^{i} \left[ \sum_{j=3m}^{120m} i_{t}^{i,t+j} + \sum_{j=3m}^{120m} i_{t}^{US,t+j} + \sum_{j=1wk}^{12m} stdev_{t}^{i,t+\mathrm{j}} + \sum_{j=1wk}^{12m} skew_{t}^{i,t+j} + \sum_{j=1wk}^{12m} Kurt_{t}^{i,t+j} \right] + \varepsilon_{t+3m}^{i}. \quad (1.13)$$

**Table 1.3**

For comparison, plots of the actual values of currency returns versus fitted values from standard UIP regressions (1.11), high moment regressions (1.12), and term structure regressions (1.13), are shown in figure (1.3). Even the UIP regression has a high adjusted R-squared due to the overlapping data issue and break dates;[19] however, we care about the relative R-squared among these three regressions. These plots show that considered with the standard UIP regression, accounting for higher order moment risks and term structure information in expectations substantially improves the model fit. The condensed results of these regressions are recorded in table (1.3), which consistently and substantially shows explanatory power improvement from the

[19] We will deal with these issues later in section 1.5.

standard UIP to term structure regression. For example, the adjusted R-squared increases from 23% to 66% for AUDUSD, from 15% to 53% for EURUSD, and from 22% to 54% for USDJPY.

**Figure 1.3**

1.4.2 *Time-Varying Parameters*

Another implication from figure (1.3) is that adding term structure information improves explanatory power most substantially during a crisis period. As suggested by structural breaks and time-varying behavior of these option-implied moments and currency returns, this section runs rolling regressions, running regressions (1.14), (1.15), and (1.16) without break dates in a rolling window of 12 months. As shown in figure (1.4), these option-implied high moments and their term structures consistently and prominently improved explanatory power on currency dynamics, particularly during the 2001 and 2008 crisis period. These findings may imply that option, and term structure information is particularly helpful when there is market turmoil. Furthermore, we record coefficients of option implied moments in rolling regression (1.15) and find that coefficients are time-varying, as shown in figure (1.5). This further implies different informational roles of option and term structure in exchange rate dynamics during different time regimes.

$$s_{t+3m}^{i} - s_{t}^{i} = \alpha^{i} + \beta\left(f_{t}^{i,t+3m} - s_{t}^{i}\right) + \varepsilon_{t+3m}^{i}, \quad (1.14)$$

$$s_{t+3m}^{i} - s_{t}^{i} = \alpha^{i} + \beta_{1}^{i}\left(f_{t}^{i,t+3m} - s_{t}^{i}\right) + \beta_{2}^{i} stdev_{t}^{i,t+3m} + \beta_{3}^{i} skew_{t}^{i,t+3m} + \beta_{4}^{i} kurt_{t}^{i,t+3m} + \varepsilon_{t+3m}^{i}, \quad (1.15)$$

$$s_{t+3m}^{i} - s_{t}^{i} = \alpha^{i} + \beta_{1,\dots,6}^{i} \sum_{p=1}^{6} PC_{p}^{i} \left[ \sum_{j=1}^{7} \left( f_{t}^{i,t+j} - s_{t}^{i} \right) + \sum_{j=1}^{7} stdev_{t}^{i,t+\mathrm{j}} + \sum_{j=1}^{7} skew_{t}^{i,t+j} + \sum_{j=1}^{7} Kurt_{t}^{i,t+j} \right] + \varepsilon_{t+3m}^{i}. \quad (1.16)$$

**Figure 1.4**

**Figure 1.5**

## 1.5 Robustness Check

To deal with potential correlation issues over these option-implied moments and their term structures, we perform robustness checks through variable selection approaches of LARS and Bayesian Moving Average (BMA), which are presented in this section. As shown in table (1.4), variables selected consistently spread over different moments and different maturities, implying that high moments and term structure are indeed informative. This is backed up by a principal component analysis as well, where principal components load on different moments and different maturities.

**Table 1.4**

To deal with a potential overlapping data issue that would inflate R-squared in the regression, we run regressions using non-overlapping data by using the first-day data of each month and one-month currency return and present them in this section. As shown in table (1.5), the explanatory power of the three regressions is indeed lower, but they keep the same ranking of the term structure regression being the highest and UIP regression the lowest. In addition, the term structure regression consistently shows joint significance for all currency pairs.

$$s_{t+1m}^{i} - s_{t}^{i} = \alpha^{i} + \beta_{1,2,3}^{i}\left(D1^{i} + D2^{i} + D3^{i}\right) + \beta_{4}^{i}\left(f_{t}^{i,t+1m} - s_{t}^{i}\right) + \beta_{5,6,7}^{i}\left(D1^{i} + D2^{i} + D3^{i}\right)\left(f_{t}^{i,t+1m} - s_{t}^{i}\right) + \varepsilon_{t+1m}^{i}. \quad (1.17a)$$

$$s_{t+1m}^{i} - s_{t}^{i} = \alpha^{i} + \beta_{1,2,3}^{i}\left(D1^{i} + D2^{i} + D3^{i}\right) + \left[\beta_{4}^{i}\left(f_{t}^{i,t+1m} - s_{t}^{i}\right) + \beta_{5}^{i} stdev_{t}^{i,t+1m} + \beta_{6}^{i} skew_{t}^{i,t+1m} + \beta_{7}^{i} kurt_{t}^{i,t+1m}\right] + \beta_{8,\dots,19}^{i}\left(D1^{i} + D2^{i} + D3^{i}\right)\left[\left(f_{t}^{i,t+1m} - s_{t}^{i}\right) + stdev_{t}^{i,t+1m} + skew_{t}^{i,t+1m} + kurt_{t}^{i,t+1m}\right] + \varepsilon_{t+1m}^{i}. \quad (1.17b)$$

$$s_{t+1m}^{i} - s_{t}^{i} = \alpha^{i} + \beta_{1,2,3}^{i}\left(D1^{i} + D2^{i} + D3^{i}\right) + \beta_{4,\dots,9}^{i} \sum_{p=1}^{6} PC_{p}^{i} \left[\sum_{j=3m}^{120m} i_{t}^{i,t+j} + \sum_{j=3m}^{120m} i_{t}^{US,t+j} + \sum_{j=1wk}^{12m} stdev_{t}^{i,t+j} + \sum_{j=1wk}^{12m} skew_{t}^{i,t+j} + \sum_{j=1wk}^{12m} Kurt_{t}^{i,t+j}\right] + \beta_{10,\dots,27}^{i}\left(D1^{i} + D2^{i} + D3^{i}\right) \sum_{p=1}^{6} PC_{p}^{i} \left[\sum_{j=3m}^{120m} i_{t}^{i,t+j} + \sum_{j=3m}^{120m} i_{t}^{US,t+j} + \sum_{j=1wk}^{12m} stdev_{t}^{i,t+j} + \sum_{j=1wk}^{12m} skew_{t}^{i,t+j} + \sum_{j=1wk}^{12m} Kurt_{t}^{i,t+j}\right] + \varepsilon_{t+1m}^{i}. \quad (1.17c)$$

**Table 1.5**

In addition, we check the correlation between these option-implied moments and conventional quotes. In the FX o-t-c option market, prices are quoted in combinations rather than simple call and put options. The most common option combinations are at-the-money (ATM)[20] straddle, risk reversals (RR), and Vega-weighted butterflies (VWB). An ATM straddle is the sum of a base currency call and a base currency put, both struck at the current forward rate. An RR is set up when one buys a base currency call and sells a base currency put with a symmetric delta ($\delta$). Finally, a VWB is built by buying a symmetric delta strangle and selling an ATM straddle.[21] The $25\delta$ combination is the most traded option. The definitions of the three option combinations are as follows:[22]

$$\sigma_{ATM,\tau} = \sigma_{0\delta,\tau} = \sigma_{50\delta c,\tau} + \sigma_{50\delta p,\tau}, \quad (1.18a)$$

$$\sigma_{25\delta RR,\tau} = \sigma_{25\delta c,\tau} - \sigma_{25\delta p,\tau}, \quad (1.18b)$$

$$\sigma_{25\delta VWB,\tau} = \frac{\sigma_{25\delta c,\tau} + \sigma_{25\delta p,\tau}}{2} - \sigma_{ATM,\tau}. \quad (1.18c)$$

The ATM straddle, risk reversal, and strangle are usually interpreted as short cut indicators of volatility, skewness, and kurtosis of the perceived conditional distribution of exchange rate movements. As shown in table (1.6), the ATM straddle is, overall, a good proxy for volatility. The risk reversal works fine to proxy for skewness in a short maturity; however, its ability to proxy

[20] ATM here means the delta ($\delta$) of the option combination is zero. That is, the option combination is "delta-neutral".

[21] In a strangle, you buy an out of the money call and an equally out of the money put.

[22] Table (1.1B) contains sample option price quotes for standard combinations and standard maturities.

decreases as the maturity gets longer. It seems that the butterfly strangle does not do a good job proxying for the kurtosis, particularly in the long maturity.

**Table 1.6**

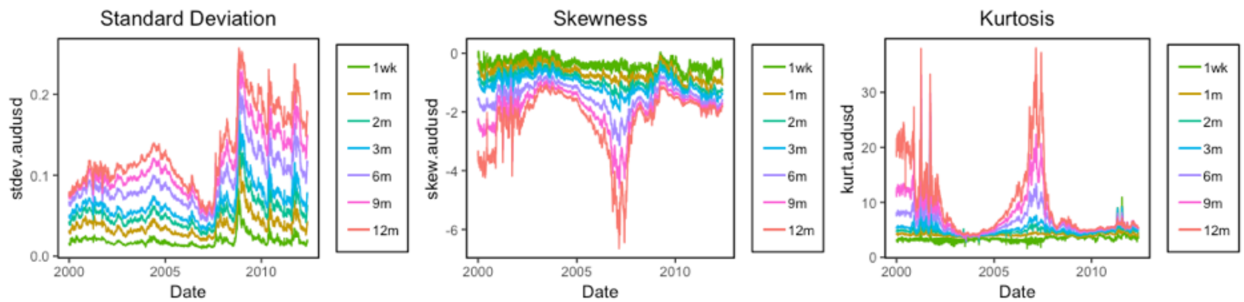
## 1.6 CONCLUSION

This paper has documented a robust ability of FX options-implied measures of higher moment risks to explain subsequent currency returns. We also find that the term structure of such risks, capturing forward-looking property of the exchange rate, add further explanatory power. Our findings suggest that expectation and risk should be given more careful consideration in the structural modeling and empirical testing of exchange rate models. In particular, our results support the existence of different time regimes and the information in these options-implied measures are particularly useful during market turmoil.

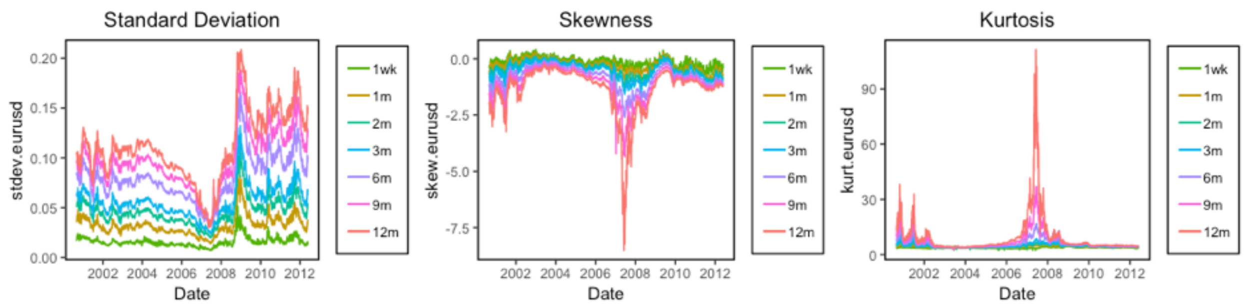
This paper can be extended in several directions that are useful to academics, monetary policy officials, and investment professionals. First, how useful is the option-based information for out-of-sample forecasting of the exchange rate. The ability to accurately forecast exchange rate movements for many purposes, including determining the future value of foreign denominated debt payments and hedging for investment managers exploiting international investment opportunities. My chapter 2 will explore a trading strategy and identified a potential risk factor through the information in FX option-implied moments and their term structure. Second, we have performed a principal component analysis and other variable selection approaches, but there may be more efficient indicators, such as the corridor method (Andersen et al., 2015), which can condense volatility and asymmetry information into a single index. My chapter 2 will introduce and apply this method on FX options to construct a new FX risk index. Third, our results are based on risk-neutral probability measurement, and Ross (2015) proposed that physical probability may even improve predictive power. I have a co-authored working paper applying the recovery theorem to derive physical probability measurements and examine the performance (Chen et al., 2019). Lastly, an empirical analysis of the macroeconomic variables and events that drive the FX option-implied moments would further shed light on the link between exchange rates and macroeconomic fundamentals, and my chapter 3 will explore this.

**Figure 1.1: Time Series Evolution of Currency Option-Implied Moments by Maturity**[23]

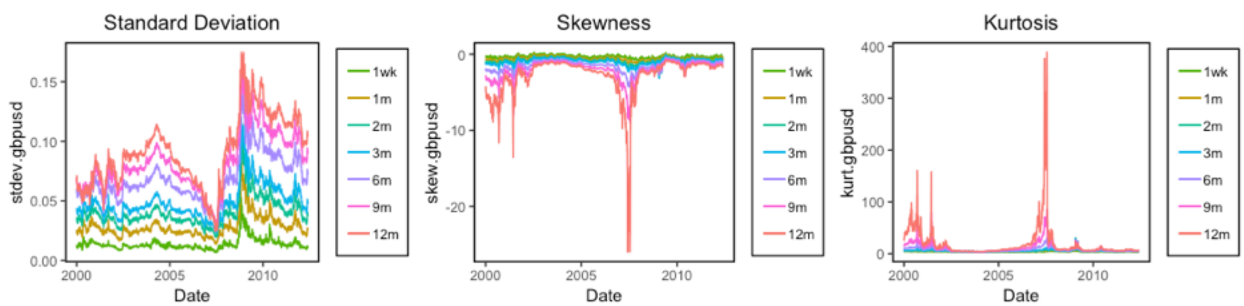
**a. AUSUSD**




**b. EURUSD**

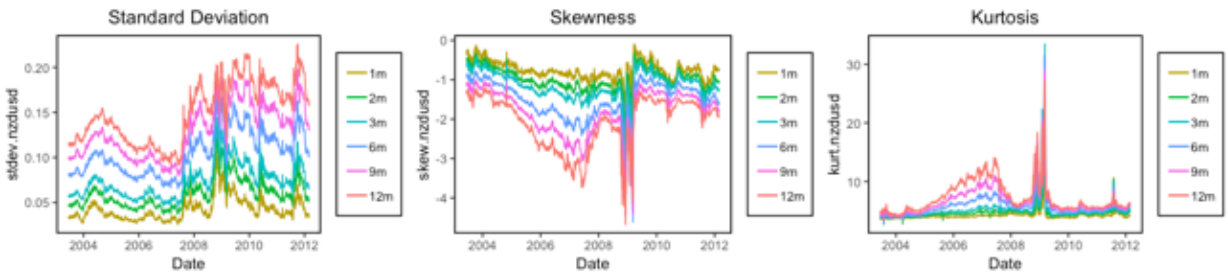



**c. GBPUSD**

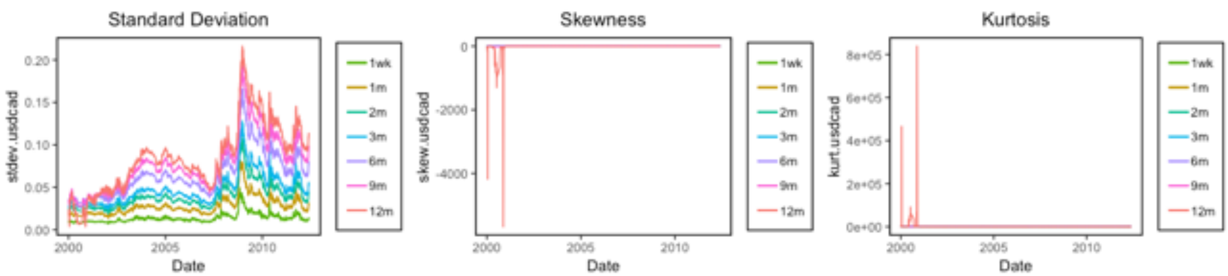



[23] For USDCAD with maturity of 12 months, there are some extreme values derived for the moments of kurtosis and skewness accompanied with very small standard deviation during the early 2000s. All these values are kept throughout the whole analysis.

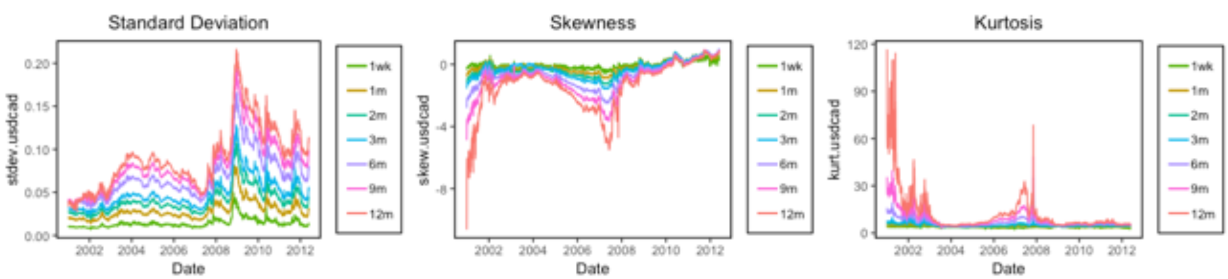
## d. NZDUSD




## e1. USDCAD (full sample starting from 2000)




## e2. USDCAD (starting from 2001)




## f. USDJPY

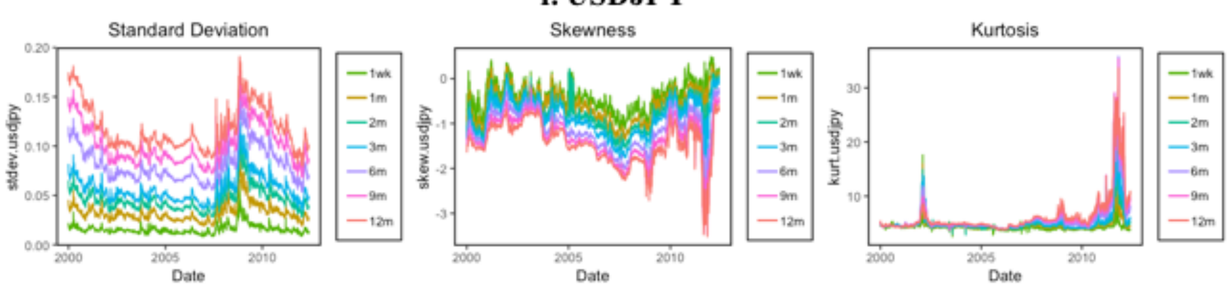
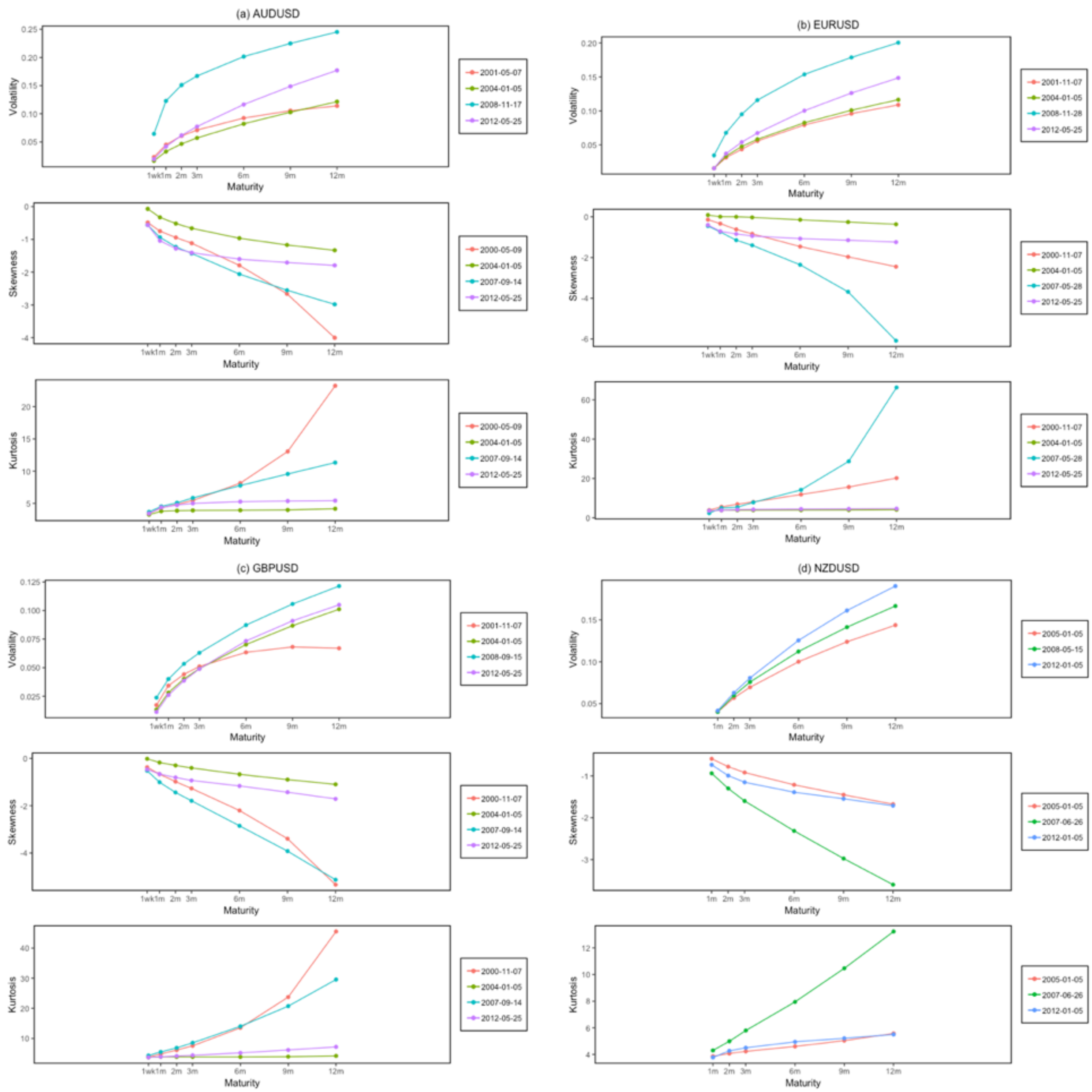


**Figure 1.2: Term Structure of Currency Option-Implied Moments on Representative Days**

The horizontal axis is maturity ranging from 1 week to 12 months.



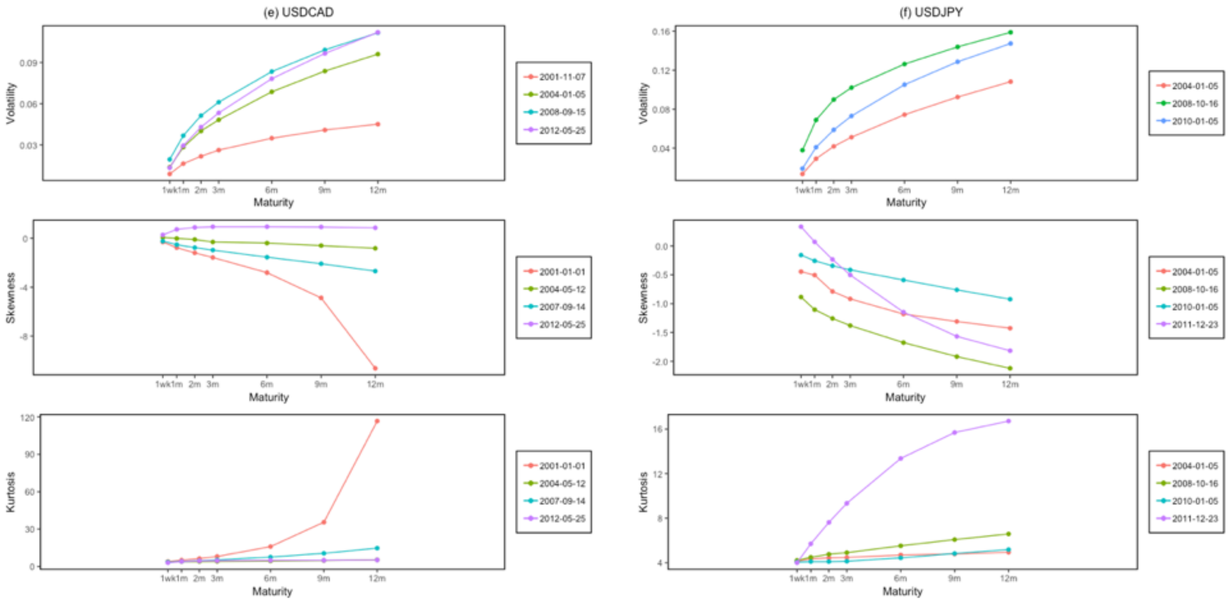
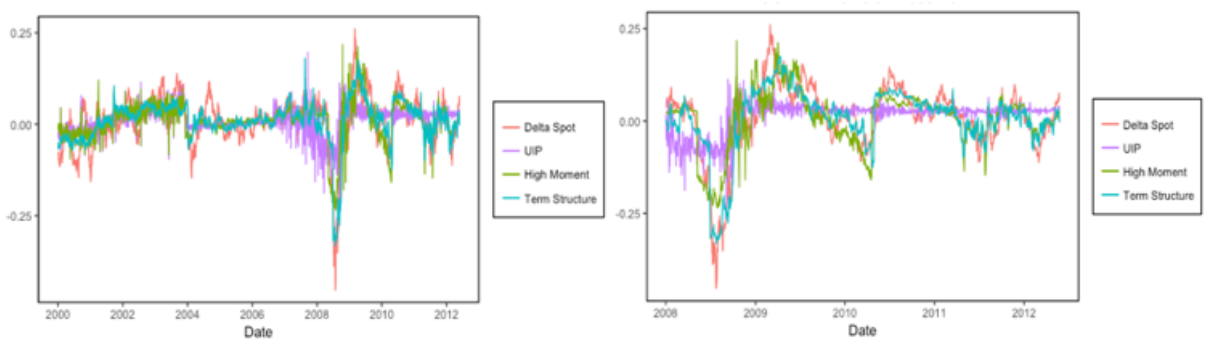

(e) USDCAD
Volatility
Maturity
1wk 1m 2m 3m 6m 9m 12m
2001-11-07
2004-01-05
2008-09-15
2012-05-25
Skewness
2001-01-01
2004-05-12
2007-09-14
2012-05-25
Kurtosis
(f) USDJPY
2004-01-05
2008-10-16
2010-01-05
2011-12-23

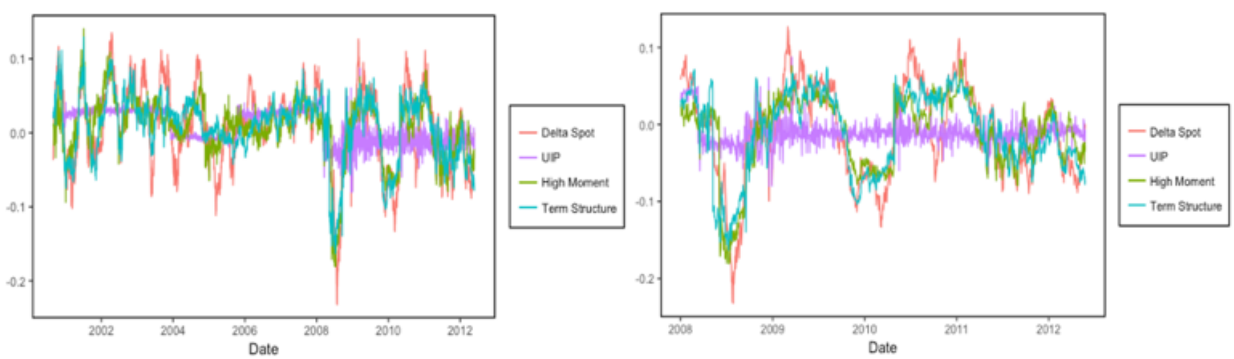
**Figure 1.3: Quarterly Currency Returns on Term Structure of 1st-4th Moments**

"Delta Spot" plots actual currency return. "UIP", "High Moment", and "Term Structure" plot fitted values of currency returns by equations (1.11), (1.12), and (1.13), respectively.

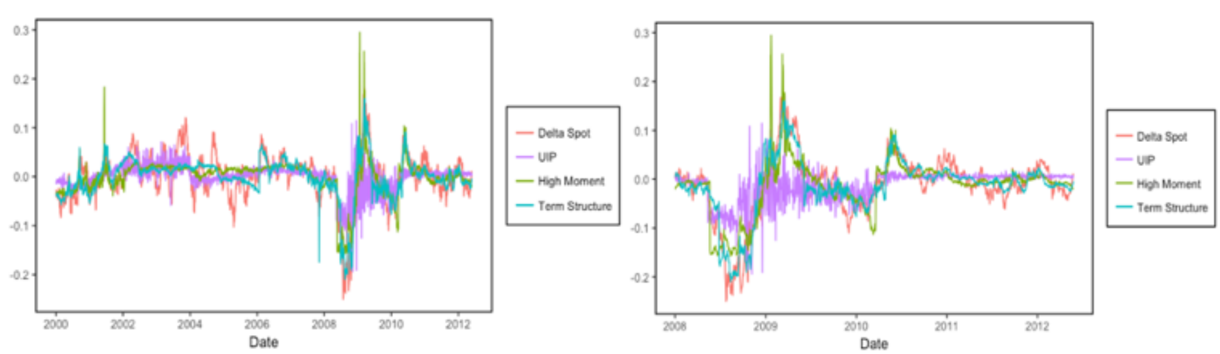
**(a) AUDUSD (left: full sample; right: 2008-2012)**



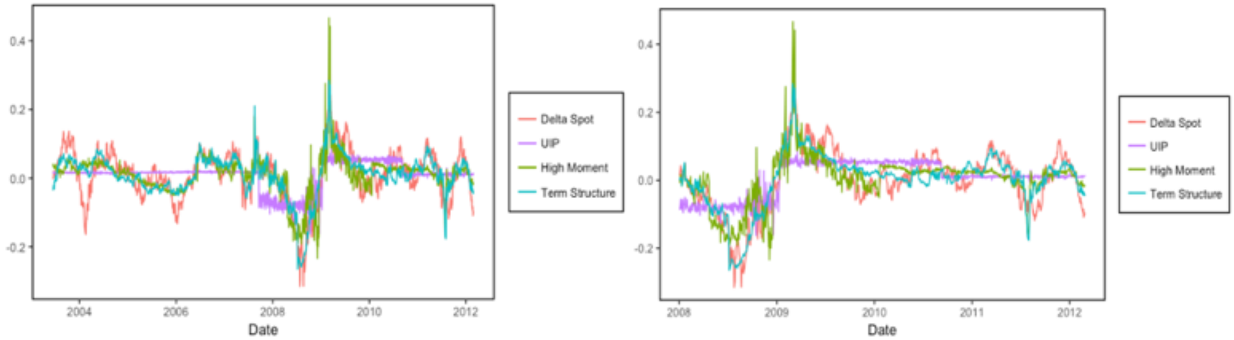

**(b) EURUSD (left: full sample; right: 2008-2012)**



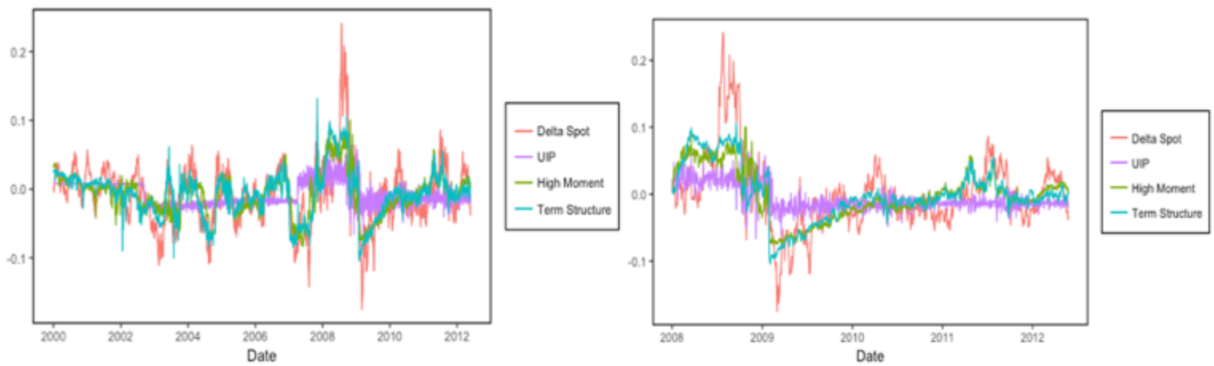

**(c) GBPUSD (left: full sample; right: 2008-2012)**



**(d) NZDUSD (left: full sample; right: 2008-2012)**




**(e) USDCAD (left: full sample; right: 2008-2012)**




**(f) USDJPY (left: full sample; right: 2008-2012)**

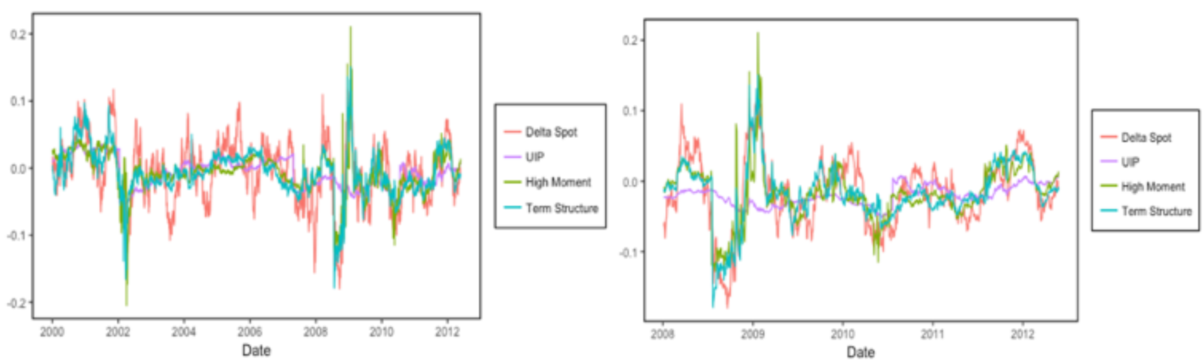


**Figure 1.4: Adjusted R-squared in Rolling Window**

“UIP”, “High Moment”, and “Term Structure” plot adjusted R-squared in a rolling window by equations (1.14), (1.15), and (1.16), respectively.

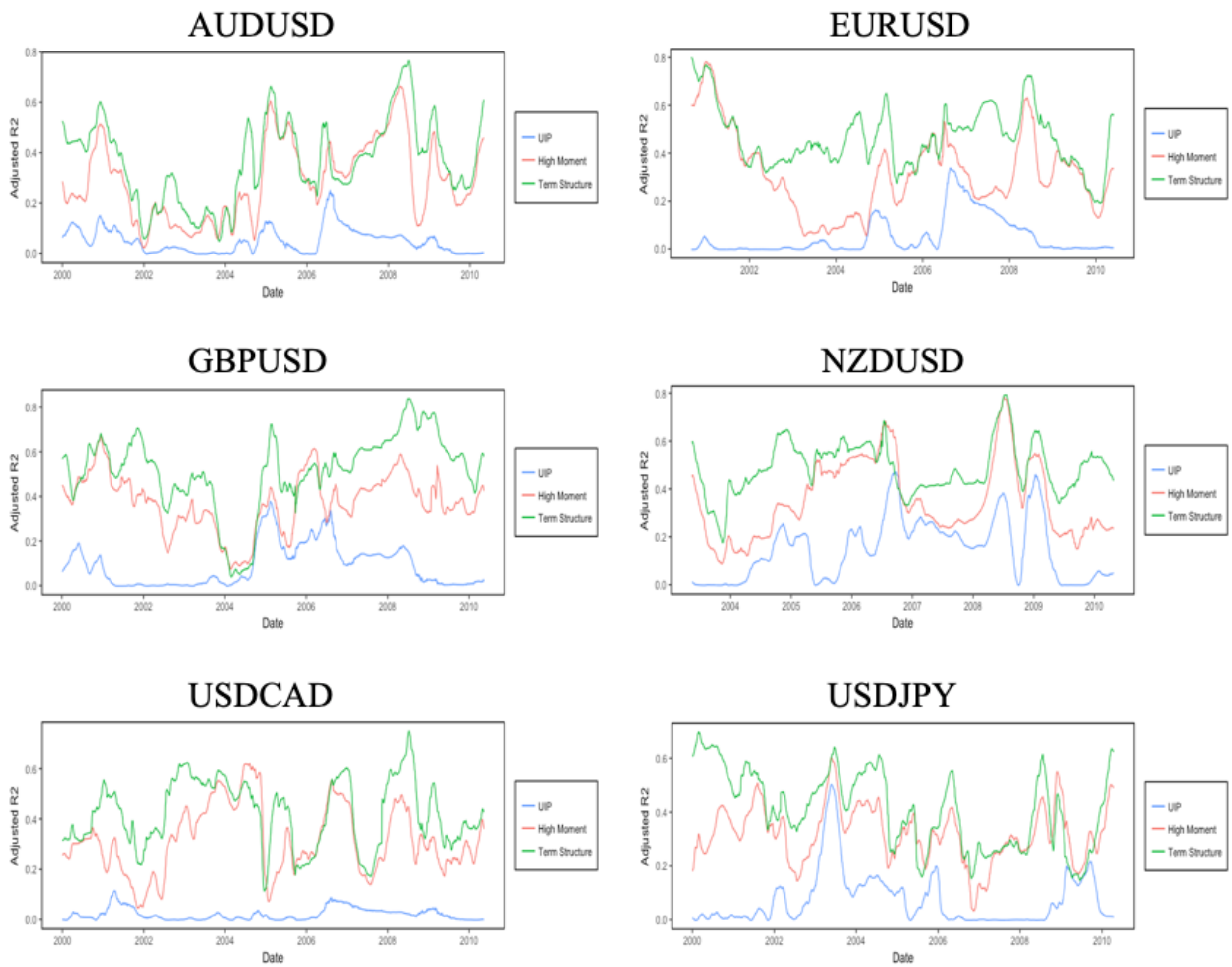


**Figure 1.5: Time-Varying Coefficients of 1st-4th Moments**

FPP is the coefficient of the forward rate in the UIP regression (1.2). Mean, Std, Skew, and Kurt are coefficients of the 1st-4th moments in the High Moment regression (1.12).

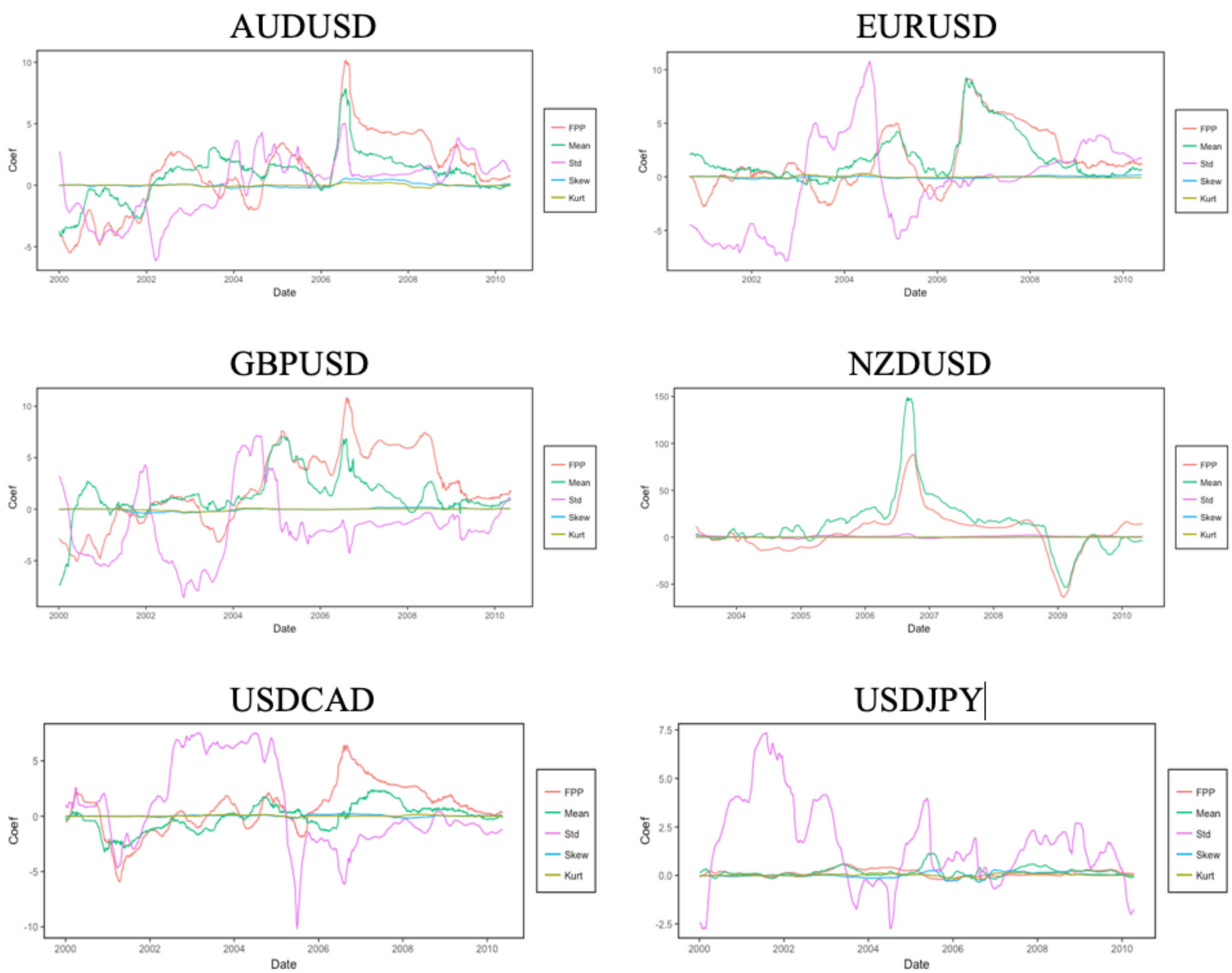


**Table 1.1: O-T-C Markets Statistics and Conventions**

"ATM" is an at-the-money straddle; 25D RR and 10D RR are 25%- and 10%- delta risk reversals, respectively; 25D VWB and 10D VWB are 25%- and 10%- delta Vega-weighted butterflies, respectively. The numbers in Table 1C are from the Bank of International Settlements (2013).

**A. Quoting Conventions in Over-The-Counter (OTC) Currency Options Market**

| Symbol | Definition | Base currency | Domestic currency | Negative Skew means |
|---|---|---|---|---|
| AUDUSD | USD per AUD | AUD | USD | AUD depreciation |
| EURUSD | USD per EUR | EUR | USD | EUR depreciation |
| GBPUSD | USD per GBP | GBP | USD | GBP depreciation |
| NZDUSD | USD per NZD | NZD | NZD | NZD depreciation |
| USDCAD | CAD per USD | USD | CAD | CAD appreciation |
| USDJPY | JPY per USD | USD | JPY | JPY appreciation |

**B. Sample Annualized Implied Volatilities**

| Maturity | ATM | 25D RR | 25D VWB | 10D RR | 10D VWB |
|---|---|---|---|---|---|
| 1 Week | 7.352 | -0.495 | 0.131 | -0.847 | 0.379 |
| 1 Month | 6.851 | -0.347 | 0.136 | -0.584 | 0.389 |
| 2 Month | 6.851 | -0.366 | 0.157 | -0.619 | 0.449 |
| 3 Month | 6.851 | -0.396 | 0.162 | -0.663 | 0.485 |
| 6 Month | 6.901 | -0.426 | 0.187 | -0.703 | 0.540 |
| 9 Month | 7.051 | -0.446 | 0.197 | -0.743 | 0.571 |
| 12 Month | 6.901 | -0.426 | 0.187 | -0.703 | 0.540 |

**C. Average Daily Turnover in Currency Market (in billions of US dollar)**

| | 1998 | 2001 | 2004 | 2007 | 2010 | 2013 |
|---|---|---|---|---|---|---|
| Spot FX Transaction | 568 | 386 | 631 | 1005 | 1488 | 2046 |
| Percent Change | N/A | -32 | 63.5 | 59.3 | 48.3 | 37.5 |
| **FX Derivatives** | | | | | | |
| Outright Forwards | 128 | 130 | 209 | 362 | 475 | 680 |
| FX Swaps | 734 | 656 | 954 | 1714 | 1759 | 2228 |
| **Options and other products** | **87** | **60** | **119** | **212** | **207** | **337** |
| Percentage Change | N/A | -31 | 98.3 | 83 | -2.4 | 62.8 |
| Exchange Traded Derivatives | 11 | 12 | 26 | 80 | 155 | 160 |

**Table 1.2: Summary Statistics of Option-Implied Moments**

"Stdev", "Skew", and "Kurt" are the implied standard deviation, skewness, and kurtosis of the risk-neutral distribution of $log\frac{S_{t+\tau}}{S_t}$. "Obs" is the number of observations. All values are annualized.

**(a) AUDUSD**

| | 1WK | 1M | 2M | 3M | 6M | 9M | 12M |
|---|---|---|---|---|---|---|---|
| **STDEV** | | | | | | | |
| Mean | 0.0188 | 0.0373 | 0.0529 | 0.0648 | 0.0928 | 0.1141 | 0.1308 |
| Median | 0.0172 | 0.0347 | 0.0496 | 0.0604 | 0.0845 | 0.1028 | 0.1167 |
| Maximum | 0.0834 | 0.1381 | 0.1686 | 0.1802 | 0.2132 | 0.2372 | 0.2573 |
| Minimum | 0.0075 | 0.0182 | 0.0257 | 0.0316 | 0.0425 | 0.0491 | 0.0524 |
| Stdev | 0.0076 | 0.0143 | 0.0186 | 0.0216 | 0.0295 | 0.0375 | 0.0457 |
| AR(1) | 0.9817 | 0.9911 | 0.9931 | 0.9946 | 0.9968 | 0.9976 | 0.9983 |
| | | | | | | | |
| **SKEW** | | | | | | | |
| Mean | -0.3774 | -0.7011 | -0.9295 | -1.1041 | -1.4999 | -1.8586 | -2.2619 |
| Median | -0.3721 | -0.7384 | -0.9732 | -1.1452 | -1.4975 | -1.7435 | -1.9493 |
| Maximum | 0.1813 | -0.0752 | -0.2683 | -0.4091 | -0.7360 | -0.9374 | -1.0669 |
| Minimum | -1.1602 | -1.6349 | -2.0175 | -2.4104 | -3.1362 | -4.5953 | -6.6528 |
| Stdev | 0.2023 | 0.2512 | 0.2823 | 0.3137 | 0.4378 | 0.6600 | 1.0177 |
| AR(1) | 0.8801 | 0.9772 | 0.9846 | 0.9875 | 0.9921 | 0.9952 | 0.9961 |
| | | | | | | | |
| **KURT** | | | | | | | |
| Mean | 3.3568 | 4.1610 | 4.6681 | 5.0835 | 6.1728 | 7.4828 | 9.4609 |
| Median | 3.3418 | 4.0836 | 4.5734 | 4.9344 | 5.5186 | 5.9216 | 6.3785 |
| Maximum | 13.7526 | 19.3200 | 22.3733 | 24.3632 | 28.7954 | 33.1373 | 38.0832 |
| Minimum | 1.5957 | 3.5322 | 2.7013 | 3.7164 | 2.9316 | 3.3647 | 3.9493 |
| Stdev | 0.4814 | 0.5739 | 0.8304 | 1.0858 | 2.0633 | 3.6300 | 6.3483 |
| AR(1) | 0.7016 | 0.8286 | 0.8957 | 0.9324 | 0.9737 | 0.9880 | 0.9931 |
| | | | | | | | |
| Obs | 3451 | 3463 | 3414 | 3425 | 3326 | 3260 | 3227 |

**(b) EURUSD**

| | 1WK | 1M | 2M | 3M | 6M | 9M | 12M |
|---|---|---|---|---|---|---|---|
| **STDEV** | | | | | | | |
| Mean | 0.0159 | 0.0319 | 0.0460 | 0.0565 | 0.0806 | 0.0982 | 0.1111 |
| Median | 0.0150 | 0.0303 | 0.0444 | 0.0550 | 0.0787 | 0.0952 | 0.1078 |
| Maximum | 0.0521 | 0.0894 | 0.1158 | 0.1322 | 0.1659 | 0.1879 | 0.2088 |
| Minimum | 0.0072 | 0.0140 | 0.0196 | 0.0238 | 0.0312 | 0.0331 | 0.0303 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Stdev | 0.0049 | 0.0098 | 0.0132 | 0.0159 | 0.0222 | 0.0280 | 0.0338 |
| AR(1) | 0.9787 | 0.9912 | 0.9933 | 0.9948 | 0.9967 | 0.9974 | 0.9981 |
| | | | | | | | |
| **SKEW** | | | | | | | |
| Mean | -0.1343 | -0.3097 | -0.4395 | -0.5447 | -0.8167 | -1.0745 | -1.3749 |
| Median | -0.1242 | -0.2810 | -0.3995 | -0.4883 | -0.7283 | -0.9189 | -1.1166 |
| Maximum | 0.4114 | 0.2897 | 0.1395 | 0.0517 | -0.0720 | -0.1504 | -0.2695 |
| Minimum | -0.7786 | -1.0529 | -1.5375 | -1.6239 | -3.0697 | -4.3475 | -8.5094 |
| Stdev | 0.2037 | 0.2597 | 0.2951 | 0.3353 | 0.4749 | 0.6715 | 1.0406 |
| AR(1) | 0.9356 | 0.9836 | 0.9877 | 0.9928 | 0.9916 | 0.9928 | 0.9956 |
| | | | | | | | |
| **KURT** | | | | | | | |
| Mean | 3.6499 | 4.1459 | 4.5225 | 4.8724 | 5.8779 | 7.1912 | 9.5703 |
| Median | 3.5661 | 3.9196 | 4.1756 | 4.3752 | 4.8498 | 5.4132 | 5.7793 |
| Maximum | 16.0332 | 18.2225 | 20.0579 | 21.5528 | 25.8624 | 37.0318 | 111.4632 |
| Minimum | 2.2998 | 3.5290 | 2.8120 | 3.7562 | 2.8297 | 2.8647 | 3.9370 |
| Stdev | 0.5336 | 0.7661 | 1.0368 | 1.3296 | 2.4808 | 4.6612 | 10.8715 |
| AR(1) | 0.7375 | 0.8954 | 0.9413 | 0.9654 | 0.9848 | 0.9913 | 0.9899 |
| | | | | | | | |
| Obs | 3464 | 3297 | 3427 | 3431 | 3339 | 3273 | 3233 |

**(c) GBPUSD**

| | **1WK** | **1M** | **2M** | **3M** | **6M** | **9M** | **12M** |
|---|---|---|---|---|---|---|---|
| **STDEV** | | | | | | | |
| Mean | 0.0136 | 0.0278 | 0.0396 | 0.0485 | 0.0685 | 0.0824 | 0.0919 |
| Median | 0.0124 | 0.0255 | 0.0366 | 0.0450 | 0.0640 | 0.0784 | 0.0897 |
| Maximum | 0.0530 | 0.0894 | 0.1086 | 0.1197 | 0.1444 | 0.1618 | 0.1747 |
| Minimum | 0.0063 | 0.0137 | 0.0194 | 0.0232 | 0.0295 | 0.0300 | 0.0242 |
| Stdev | 0.0050 | 0.0092 | 0.0121 | 0.0142 | 0.0192 | 0.0239 | 0.0294 |
| AR(1) | 0.9843 | 0.9925 | 0.9941 | 0.9953 | 0.9970 | 0.9975 | 0.9980 |
| | | | | | | | |
| **SKEW** | | | | | | | |
| Mean | -0.2877 | -0.5506 | -0.7608 | -0.9388 | -1.4229 | -1.9798 | -2.8477 |
| Median | -0.2879 | -0.5312 | -0.7056 | -0.8654 | -1.2732 | -1.6513 | -2.0118 |
| Maximum | 0.2855 | 0.0971 | -0.0239 | -0.1283 | -0.3926 | -0.6009 | -0.7741 |
| Minimum | -2.1662 | -2.9000 | -3.1508 | -3.1240 | -5.0469 | -8.9576 | -26.0525 |
| Stdev | 0.2003 | 0.2567 | 0.3276 | 0.4024 | 0.6857 | 1.2135 | 2.6949 |
| AR(1) | 0.9399 | 0.9690 | 0.9800 | 0.9860 | 0.9934 | 0.9943 | 0.9895 |
| | | | | | | | |
| **KURT** | | | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Mean | 3.8641 | 4.3990 | 4.9675 | 5.5518 | 7.5662 | 10.9365 | 19.3050 |
| Median | 3.7901 | 4.1002 | 4.4164 | 4.7820 | 6.0429 | 7.3728 | 8.6416 |
| Maximum | 25.1887 | 29.4668 | 30.1066 | 29.2852 | 44.8657 | 85.4347 | 389.0710 |
| Minimum | 2.5103 | 3.6052 | 2.7714 | 3.7906 | 3.2720 | 3.2100 | 4.0963 |
| Stdev | 0.6951 | 1.1250 | 1.5755 | 2.0175 | 4.0469 | 9.4686 | 32.4054 |
| AR(1) | 0.7588 | 0.8904 | 0.9336 | 0.9559 | 0.9805 | 0.9866 | 0.9781 |
| Obs | 3453 | 3465 | 3416 | 3427 | 3328 | 3262 | 3229 |

**(d) NZDUSD**

| | **1M** | **2M** | **3M** | **6M** | **9M** | **12M** |
|---|---|---|---|---|---|---|
| **STDEV** | | | | | | |
| Mean | 0.0413 | 0.0590 | 0.0727 | 0.1052 | 0.1299 | 0.1498 |
| Median | 0.0376 | 0.0549 | 0.0692 | 0.1036 | 0.1286 | 0.1488 |
| Maximum | 0.1161 | 0.1361 | 0.1477 | 0.1705 | 0.1979 | 0.2260 |
| Minimum | 0.0217 | 0.0327 | 0.0428 | 0.0655 | 0.0796 | 0.0913 |
| Stdev | 0.0129 | 0.0162 | 0.0183 | 0.0237 | 0.0289 | 0.0338 |
| AR(1) | 0.9873 | 0.9895 | 0.9914 | 0.9937 | 0.9953 | 0.9962 |
| **SKEW** | | | | | | |
| Mean | -0.7504 | -0.9816 | -1.1543 | -1.5119 | -1.8006 | -2.0857 |
| Median | -0.7764 | -1.0080 | -1.1827 | -1.4622 | -1.6770 | -1.8767 |
| Maximum | -0.0915 | -0.2864 | -0.4560 | -0.7769 | -1.0137 | -1.1989 |
| Minimum | -2.3836 | -3.5882 | -4.3344 | -4.6094 | -4.4530 | -4.6761 |
| Stdev | 0.2283 | 0.2867 | 0.3393 | 0.4549 | 0.5490 | 0.6474 |
| AR(1) | 0.9505 | 0.9573 | 0.9659 | 0.9838 | 0.9904 | 0.9934 |
| **KURT** | | | | | | |
| Mean | 4.1684 | 4.6510 | 5.0110 | 5.7449 | 6.4331 | 7.2650 |
| Median | 4.0079 | 4.4610 | 4.7733 | 5.3184 | 5.7195 | 6.1627 |
| Maximum | 24.4194 | 30.8459 | 33.4668 | 31.6687 | 29.2417 | 27.2081 |
| Minimum | 3.4835 | 2.6452 | 3.6875 | 2.8973 | 3.3096 | 4.0517 |
| Stdev | 1.0024 | 1.4021 | 1.6197 | 1.9205 | 2.2009 | 2.6345 |
| AR(1) | 0.8298 | 0.8889 | 0.9170 | 0.9566 | 0.9735 | 0.9838 |
| Obs | 2506 | 2460 | 2465 | 2370 | 2304 | 2269 |

**(e) USDCAD**[24]

| | 1WK | 1M | 2M | 3M | 6M | 9M | 12M | 12M (start 2001) |
|---|---|---|---|---|---|---|---|---|
| **STDEV** | | | | | | | | |
| Mean | 0.0136 | 0.0273 | 0.0383 | 0.0465 | 0.0646 | 0.0767 | 0.0860 | 0.0900 |
| Median | 0.0124 | 0.0250 | 0.0349 | 0.0428 | 0.0602 | 0.0730 | 0.0827 | 0.0866 |
| Maximum | 0.0495 | 0.0813 | 0.1083 | 0.1283 | 0.1664 | 0.1935 | 0.2161 | 0.2161 |
| Minimum | 0.0067 | 0.0134 | 0.0185 | 0.0231 | 0.0273 | 0.0211 | 0.0036 | 0.0280 |
| Stdev | 0.0054 | 0.0107 | 0.0147 | 0.0178 | 0.0255 | 0.0324 | 0.0389 | 0.0366 |
| AR(1) | 0.9888 | 0.9948 | 0.9962 | 0.9970 | 0.9979 | 0.9984 | 0.9987 | 0.9986 |
| **SKEW** | | | | | | | | |
| Mean | -0.0090 | -0.1457 | -0.2706 | -0.3748 | -0.8145 | -1.5320 | -11.0594 | -1.3872 |
| Median | -0.0448 | -0.2136 | -0.3224 | -0.3106 | -0.6480 | -0.8608 | -1.1137 | -1.0490 |
| Maximum | 1.0258 | 0.9045 | 0.9365 | 0.9718 | 0.9659 | 0.9447 | 0.9144 | 0.9144 |
| Minimum | -0.6537 | -1.0097 | -1.6000 | -2.1855 | -5.2085 | -20.9009 | -5676.6188 | -10.6392 |
| Stdev | 0.2782 | 0.4150 | 0.5547 | 0.6811 | 1.1042 | 2.5392 | 140.5854 | 1.5385 |
| AR(1) | 0.9602 | 0.9930 | 0.9965 | 0.9974 | 0.9986 | 0.9961 | 1.0000 | 0.9996 |
| **KURT** | | | | | | | | |
| Mean | 4.7729 | 4.2534 | 4.8174 | 5.3653 | 7.6869 | 14.7255 | 1459.173 | 12.5339 |
| Median | 4.7641 | 4.0027 | 4.3791 | 4.6974 | 5.6739 | 6.5639 | 7.5796 | 7.0162 |
| Maximum | 22.2374 | 18.5064 | 20.5823 | 24.2180 | 37.5633 | 293.9485 | 1119973 | 116.6677 |
| Minimum | 2.3793 | 3.2718 | 3.0236 | 3.8097 | 3.1487 | 3.1711 | 4.6276 | 4.6276 |
| Stdev | 0.7855 | 0.7741 | 1.1526 | 1.5941 | 4.9831 | 26.9128 | 2.7749 | 13.6134 |
| AR(1) | 0.7947 | 0.8805 | 0.9311 | 0.9672 | 0.9905 | 0.9904 | 9.6608 | 0.9901 |
| Obs | 3453 | 3465 | 3416 | 3427 | 3328 | 3262 | 3229 | 2970 |

**(f) USDJPY**

| | 1WK | 1M | 2M | 3M | 6M | 9M | 12M |
|---|---|---|---|---|---|---|---|
| **STDEV** | | | | | | | |
| Mean | 0.0157 | 0.0322 | 0.0457 | 0.0561 | 0.0807 | 0.1005 | 0.1178 |
| Median | 0.0147 | 0.0303 | 0.0432 | 0.0528 | 0.0749 | 0.0930 | 0.1097 |
| Maximum | 0.0658 | 0.1156 | 0.1387 | 0.1468 | 0.1657 | 0.1790 | 0.1909 |
| Minimum | 0.0080 | 0.0184 | 0.0277 | 0.0344 | 0.0507 | 0.0681 | 0.0794 |

[24] USDCAD in maturity 12 months derived some extreme values of skewness and kurtosis during the year of 2000. We keep these values in our analysis, and also report the summary statistics excluding the year of 2000.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Stdev | 0.0050 | 0.0095 | 0.0123 | 0.0142 | 0.0182 | 0.0207 | 0.0228 |
| AR(1) | 0.9654 | 0.9820 | 0.9858 | 0.9894 | 0.9941 | 0.9961 | 0.9970 |
| | | | | | | | |
| **SKEW** | | | | | | | |
| Mean | -0.3564 | -0.5502 | -0.6903 | -0.8293 | -1.1064 | -1.3038 | -1.4575 |
| Median | -0.3649 | -0.5282 | -0.7022 | -0.8417 | -1.1352 | -1.3303 | -1.4652 |
| Maximum | 0.5777 | 0.4413 | 0.4741 | 0.5209 | 0.2505 | -0.2357 | -0.5644 |
| Minimum | -1.1472 | -1.6388 | -2.0512 | -2.4594 | -3.2019 | -3.4728 | -3.5206 |
| Stdev | 0.3459 | 0.4005 | 0.4376 | 0.4601 | 0.4734 | 0.4714 | 0.4675 |
| AR(1) | 0.9730 | 0.9890 | 0.9839 | 0.9926 | 0.9922 | 0.9920 | 0.9935 |
| | | | | | | | |
| **KURT** | | | | | | | |
| Mean | 4.1830 | 4.5992 | 4.9266 | 5.2264 | 5.9123 | 6.2319 | 6.3369 |
| Median | 4.0738 | 4.3275 | 4.4703 | 4.5610 | 4.7811 | 4.9380 | 5.0343 |
| Maximum | 20.3268 | 24.7504 | 28.4252 | 31.2213 | 35.7826 | 35.3878 | 33.7006 |
| Minimum | 2.5091 | 3.5347 | 2.8535 | 3.8573 | 3.6692 | 3.7279 | 3.7997 |
| Stdev | 0.8361 | 1.4173 | 1.9755 | 2.4164 | 3.3790 | 3.7695 | 3.8122 |
| AR(1) | 0.8032 | 0.9282 | 0.9568 | 0.9683 | 0.9820 | 0.9882 | 0.9910 |
| | | | | | | | |
| Obs | 3465 | 3468 | 3428 | 3430 | 3340 | 3274 | 3232 |

**Table 1.3: Quarterly Currency Returns Regressions Summary**

"UIP", "High Moment", and "Term Structure" represent regressions (1.11), (1.12), and (1.13), respectively. "Obs" is the number of observations. Adj-R2 is adjusted R-squared. P (F-stat) is the overall significance of the regression.

| | UIP | High Moment | Term Structure |
|---|---|---|---|
| **AUDUSD** | | | |
| Obs | 2979 | 2979 | 2979 |
| Adj-R2 | 0.2267 | 0.5197 | 0.6578 |
| P (F-stat) | 0.00 | 0.00 | 0.00 |
| Break Dates | 2003-12-09, 2006-08-29, 2008-10-03 | 2003-12-09, 2008-05-09, 2010-04-20 | 2004-01-07, 2008-06-29, 2010-04-30 |
| **EURUSD** | | | |
| Obs | 2910 | 2910 | 2910 |
| Adj-R2 | 0.166 | 0.5416 | 0.6214 |
| P (F-stat) | 0.00 | 0.00 | 0.00 |
| Break Dates | 2003-12-09, 2005-10-12, 2008-03-11 | 2004-11-23, 2008-06-03, 2010-04-27 | 2002-08-02, 2008-05-09, 2010-04-30 |
| **GBPUSD** | | | |
| Obs | 3010 | 3010 | 3010 |
| Adj-R2 | 0.2531 | 0.5540 | 0.6814 |
| P (F-stat) | 0.00 | 0.00 | 0.00 |
| Break Dates | 2004-01-02, 2008-05-13, 2010-03-22 | 2002-01-16, 2008-05-21, 2010-03-22 | 2006-01-25, 2008-06-27, 2010-04-29 |
| **NZDUSD** | | | |
| Obs | 2077 | 2077 | 2077 |
| Adj-R2 | 0.2634 | 0.5463 | 0.7052 |
| P (F-stat) | 0.00 | 0.00 | 0.00 |
| Break Dates | 2007-09-18, 2009-01-09, 2010-09-08 | 2006-06-12, 2008-04-23, 2010-01-20 | 2006-05-31, 2008-07-07, 2010-07-26 |
| **USDCAD** | | | |
| Obs | 2950 | 2950 | 2950 |
| Adj-R2 | 0.1431 | 0.4594 | 0.5651 |
| P (F-stat) | 0.00 | 0.00 | 0.00 |
| Break Dates | 2002-09-10, 2007-04-05, 2009-02-09 | 2003-10-10, 2006-12-11, 2009-01-29 | 2003-04-30, 2007-01-05, 2009-01-29 |
| **USDJPY** | | | |

| | | | |
|---|---|---|---|
| Obs | 2913 | 2913 | 2913 |
| Adj-R2 | 0.2236 | 0.4312 | 0.5428 |
| P (F-stat) | 0.00 | 0.00 | 0.00 |
| Break Dates | 2002-01-17, 2007-04-27, 2010-07-22 | 2002-04-03, 2008-07-18, 2010-07-15 | 2002-03-01, 2008-07-22, 2010-06-02 |

**Table 1.4: Variables Selection**

**(a) Variables Selected by BMA**

All variables listed here are of probability 100%, except for those with extra note.

| AUDUSD | EURUSD | GBPUSD | NZDUSD | USDCAD | USDJPY |
|---|---|---|---|---|---|
| Std_1m | Std_1wk | Skew_1wk | D3 | D1 | Std_6m |
| Skew_2m | Kurt_1wk | Kurt_1wk | Std_1m | D2 | Kurt_6m |
| Std_3m | Std_1m | Std_6m | Kurt_3m | D3 | Skew_9m |
| Skew_6m | Skew_6m | Std_9m | Skew_6m | y3 | Kurt_9m |
| Std_9m | Skew_9m | Kurt_9m | Std_9m | y12 | Skew_12m |
| Skew_9m | Yield_3m | Std_12m | Skew_12m | y60 | Kurt_12m |
| Kurt_9m | Yield_12m | USyield_3m | USyield_3m | D1*Kurt_3m | Yield_3m |
| USyield_3m | D1*Std_1wk | USyield_60m | Yield_12m | D1*Std_9m | D1*Kurt_2m |
| Yield_3m | D1*Std_1m | USyield_120m | Yield_120m | D1*USyield_12m | D1*Kurt_6m |
| Yield_12m | D1*Kurt_1m | Yield_12m | D1*Std_1m | D1*USyield_60m | D1*Skew_9m |
| Yield_60m | D1*Std_3m | Yield_60m | D1*Skew_6m | D2*Kurt_1m | D1*Kurt_9m |
| D1*Std_1m | D1*Skew_3m | D1*Kurt_1wk | D1*Kurt_6m | D2*Skew_2m | D1*Skew_12m |
| D1*Skew_2m | D1*Kurt_3m | D1*Std_1m | D1*Std_9m | D2*Kurt_2m | D1*Kurt_12m |
| D1*Std_3m | D1*Std_6m | D1*Kurt_1m | D1*Skew_9m | D2*Skew_6m | D1*USyield_60m |
| D1*Kurt_3m | D1*USyield_3m | D1*Std_3m | D1*Kurt_9m | D2*Kurt_6m | D1*Yield_3m |
| D1*Skew_6m | D1*USyield_12m | D1*Kurt_3m | D1*USyield_3m | D2*Std_9m | D1*Yield_12m |
| D1*Skew_9m | D1*Yield_60m | D1*Std_9m | D1*Yield_12m | D2*Skew_9m | D1*Yield_60m |
| D1*USyield_3m | D2*Kurt_1m | D1*Kurt_9m | D1*Yield_120m | D2*Kurt_9m | D1*Yield_120m |
| D1*USyield_60m | D2*Skew_2m | D1*USyield_12m | D2*Skew_1m | D2*USyield_3m | D2*Skew_1m |
| D1*USyield_120m | D2*Std_3m | D1*Yield_12m | D2*Std_6m | D2*USyield_60m | D2*Kurt_2m |
| D1*Yield_3m | D2*Skew_3m | D1*Yield_60m | D2*Skew_12m | D2*USyield_120m | D2*Std_3m |
| D1*Yield_12m | D2*Kurt_3m | D2*Skew_1wk | D2*Yield_60m | D3*Kurt_1m | D2*Std_6m |
| D1*Yield_120m | D2*Std_6m | D2*Std_1m | D2*Yield_120m | D3*Skew_2m | D2*Skew_6m |
| D2*Std_9m | D2*Skew_6m | D2*Std_3m | D3*Skew_2m | D3*Kurt_2m | D2*Kurt_9m |
| D2*Skew_12m | D2*USyield_3m | D2*Kurt_9m | D3*Kurt_2m | D3*Skew_6m | D2*Std_12m |
| D2*Kurt_12m | D2*USyield_12m | D2*Skew_12m | D3*Skew_6m | D3*Kurt_6m | D2*Skew_12m |
| D2*USyield_12m | D2*Yield_60m | D2*USyield_60m | D3*Kurt_9m | D3*Skew_9m | D2*USyield_60m (prob 86.7%) |
| D2*USyield_60m | D3*Kurt_9m | D3*Kurt_3m | D3*Std_12m | D3*USyield_60 | D3*Kurt_9m |
| D3*Yield_3m | D3*Kurt_12m | D3*Skew_12m | D3*Skew_12m | D3*yield_12m | D3*Kurt_12m |
| D3*Yield_60m | D3*Yield_60m | D3*USyield_12m | D3*USyield_12m | D3*yield_60m | D3*USyield_3m |

### (b) Variables Selected by LARS

| AUDUSD | EURUSD | GBPUSD | NZDUSD | USDCAD | USDJPY |
|---|---|---|---|---|---|
| D1 | D1 | D1 | D1 | D1 | D1 |
| D2 | D2 | D2 | D2 | D2 | D2 |
| D3 | D3 | D3 | D3 | D3 | D3 |
| Std_1wk | Std_1wk | Std_1wk | Std_1m | Std_1wk | Std_1wk |
| Skew_1wk | Skew_1wk | Skew_1wk | Skew_1m | Skew_1wk | Skew_1wk |
| Kurt_1wk | Kurt_1wk | Kurt_1wk | Kurt_1m | Kurt_1wk | Kurt_1wk |
| Std_1m | Std_1m | Std_1m | Std_2m | Std_1m | Std_1m |
| Skew_1m | Skew_1m | Skew_1m | Skew_2m | Skew_1m | Skew_1m |
| Kurt_1m | Kurt_1m | Kurt_1m | Kurt_2m | Kurt_1m | Kurt_1m |
| Std_2m | Std_2m | Std_2m | Std_3m | Std_2m | Std_2m |
| Skew_2m | Skew_2m | Skew_2m | Skew_3m | Skew_2m | Skew_2m |
| Kurt_2m | Std_3m | Kurt_2m | Kurt_3m | Kurt_2m | Kurt_2m |
| Std_3m | Skew_3m | Std_3m | Std_6m | Std_3m | Std_3m |
| Skew_3m | Kurt_3m | Skew_3m | Skew_6m | Skew_3m | Skew_3m |
| Kurt_3m | Std_6m | Kurt_3m | Kurt_6m | Kurt_3m | Kurt_3m |
| Std_6m | Kurt_6m | Std_6m | Std_9m | Std_6m | Std_6m |
| Skew_6m | Std_9m | Skew_6m | Skew_9m | Skew_6m | Skew_6m |
| Kurt_6m | Skew_9m | Kurt_6m | Kurt_9m | Kurt_6m | Kurt_6m |
| Std_9m | Kurt_9m | Std_9m | Std_12m | Std_9m | Std_9m |
| Skew_9m | Std_12m | Skew_9m | Skew_12m | Skew_9m | Skew_9m |
| Kurt_9m | Skew_12m | Kurt_9m | Kurt_12m | Kurt_9m | Kurt_9m |
| Std_12m | Kurt_12m | Std_12m | USyield_3m | USyield_3m | Std_12m |
| Skew_12m | USyield_3m | Skew_12m | USyield_12m | USyield_12m | Skew_12m |
| Kurt_12m | USyield_12m | Kurt_12m | USyield_60m | USyield_60m | Kurt_12m |
| USyield_3m | USyield_60m | USyield_3m | USyield_120m | USyield_120m | USyield_3m |
| USyield_12m | USyield_120m | USyield_12m | Yield_3m | Yield_3m | USyield_12m |
| USyield_60m | Yield_3m | USyield_60m | Yield_12m | Yield_1m | USyield_60m |
| USyield_120m | Yield_12m | USyield_120m | Yield_60m | Yield_60m | USyield_120m |
| Yield_3m | Yield_60m | Yield_3m | Yield_120m | Yield_120m | Yield_3m |
| Yield_12m | Yield_120m | Yield_12m | D1*Std_1m | D1*Std_1wk | Yield_12m |
| Yield_60m | D1*Std_1wk | Yield_60m | D1*Skew_1m | D1*Skew_1wk | Yield_60m |
| Yield_120m | D1*Skew_1wk | Yield_120m | D1*Kurt_1m | D1*Kurt_1wk | Yield_120m |
| D1*Std_1wk | D1*Kurt_1wk | D1*Std_1wk | D1*Std_2m | D1*Std_1m | D1*Std_1wk |
| D1*Skew_1wk | D1*Std_1m | D1*Skew_1wk | D1*Skew_2m | D1*Skew_1m | D1*Skew_1wk |
| D1*Kurt_1wk | D1*Skew_1m | D1*Kurt_1wk | D1*Kurt_2m | D1*Kurt_1m | D1*Kurt_1wk |
| D1*Std_1m | D1*Kurt_1m | D1*Std_1m | D1*Std_3m | D1*Std_2m | D1*Std_1m |

| | | | | | |
|---|---|---|---|---|---|
| D1*Skew_1m | D1*Std_2m | D1*Skew_1m | D1*Skew_3m | D1*Kurt_2m | D1*Skew_1m |
| D1*Kurt_1m | D1*Skew_2m | D1*Kurt_1m | D1*Kurt_3m | D1*Std_3m | D1*Kurt_1m |
| D1*Std_2m | D1*Kurt_2m | D1*Std_2m | D1*Std_6m | D1*Skew_3m | D1*Std_2m |
| D1*Skew_2m | D1*Std_3m | D1*Skew_2m | D1*Skew_6m | D1*Kurt_3m | D1*Skew_2m |
| D1*Kurt_2m | D1*Skew_3m | D1*Kurt_2m | D1*Kurt_6m | D1*Skew_6m | D1*Kurt_2m |
| D1*Std_3m | D1*Kurt_3m | D1*Std_3m | D1*Std_9m | D1*Kurt_6m | D1*Std_3m |
| D1*Skew_3m | D1*Std_6m | D1*Skew_3m | D1*Skew_9m | D1*Std_9m | D1*Skew_3m |
| D1*Kurt_3m | D1*Skew_6m | D1*Kurt_3m | D1*Kurt_9m | D1*Skew_9m | D1*Kurt_3m |
| D1*Std_6m | D1*Kurt_6m | D1*Std_6m | D1*Std_12m | D1*Kurt_9m | D1*Std_6m |
| D1*Skew_6m | D1*Std_9m | D1*Kurt_6m | D1*Skew_12m | D1*USyield_3m | D1*Skew_6m |
| D1*Kurt_6m | D1*Skew_9m | D1*Std_9m | D1*Kurt_12m | D1*USyield_12m | D1*Kurt_6m |
| D1*Std_9m | D1*Kurt_9m | D1*Skew_9m | D1*USyield_3m | D1*USyield_60m | D1*Std_9m |
| D1*Skew_9m | D1*Std_12m | D1*Kurt_9m | D1*USyield_12m | D1*USyield_120m | D1*Skew_9m |
| D1*Kurt_9m | D1*Kurt_12m | D1*Std_12m | D1*USyield_60m | D1*yield_3m | D1*Kurt_9m |
| D1*Std_12m | D1*USyield_3m | D1*Skew_12m | D1*USyield_120m | D1*yield_12m | D1*Std_12m |
| D1*Skew_12m | D1*USyield_12m | D1*Kurt_12m | D1*Yield_3m | D1*yield_60m | D1*Skew_12m |
| D1*Kurt_12m | D1*USyield_60m | D1*USyield_3m | D1*Yield_12m | D1*yield_120m | D1*Kurt_12m |
| D1*USyield_3m | D1*USyield_120m | D1*USyield_12m | D1*Yield_60m | D2*Std_1wk | D1*USyield_3m |
| D1*USyield_12m | D1*Yield_3m | D1*USyield_60m | D1*Yield_120m | D2*Skew_1wk | D1*USyield_12m |
| D1*USyield_60m | D1*Yield_12m | D1*USyield_120m | D2*Std_1m | D2*Kurt_1wk | D1*USyield_60m |
| D1*USyield_120m | D1*Yield_60m | D1*Yield_3m | D2*Skew_1m | D2*Std_1m | D1*USyield_120m |
| D1*Yield_3m | D1*Yield_120m | D1*Yield_12m | D2*Kurt_1m | D2*Skew_1m | D1*Yield_3m |
| D1*Yield_12m | D2*Std_1wk | D1*Yield_60m | D2*Std_2m | D2*Kurt_1m | D1*Yield_12m |
| D1*Yield_60m | D2*Skew_1wk | D1*Yield_120m | D2*Skew_2m | D2*Skew_2m | D1*Yield_60m |
| D1*Yield_120m | D2*Kurt_1wk | D2*Std_1wk | D2*Kurt_2m | D2*Kurt_2m | D1*Yield_120m |
| D2*Std_1wk | D2*Skew_1m | D2*Skew_1wk | D2*Std_3m | D2*Std_3m | D2*Std_1wk |
| D2*Skew_1wk | D2*Kurt_1m | D2*Kurt_1wk | D2*Skew_3m | D2*Skew_3m | D2*Skew_1wk |
| D2*Kurt_1wk | D2*Std_2m | D2*Std_1m | D2*Kurt_3m | D2*Kurt_3m | D2*Kurt_1wk |
| D2*Std_1m | D2*Skew_2m | D2*Skew_1m | D2*Std_6m | D2*Std_6m | D2*Std_1m |
| D2*Skew_1m | D2*Kurt_2m | D2*Kurt_1m | D2*Skew_6m | D2*Kurt_6m | D2*Skew_1m |
| D2*Kurt_1m | D2*Std_3m | D2*Std_2m | D2*Kurt_6m | D2*Std_9m | D2*Kurt_1m |
| D2*Std_2m | D2*Skew_3m | D2*Skew_2m | D2*Std_9m | D2*Skew_9m | D2*Std_2m |
| D2*Skew_2m | D2*Kurt_3m | D2*Kurt_2m | D2*Skew_9m | D2*Kurt_9m | D2*Skew_2m |
| D2*Kurt_2m | D2*Std_6m | D2*Std_3m | D2*Kurt_9m | D2*USyield_3m | D2*Kurt_2m |
| D2*Std_3m | D2*Skew_6m | D2*Skew_3m | D2*Std_12m | D2*USyield_12m | D2*Std_3m |
| D2*Skew_3m | D2*Kurt_6m | D2*Kurt_3m | D2*Skew_12m | D2*USyield_60m | D2*Skew_3m |
| D2*Kurt_3m | D2*Skew_9m | D2*Std_6m | D2*Kurt_12m | D2*USyield_120m | D2*Kurt_3m |
| D2*Std_6m | D2*Std_12m | D2*Skew_6m | D2*USyield_3m | D2*yield_3m | D2*Std_6m |
| D2*Skew_6m | D2*Skew_12m | D2*Kurt_6m | D2*USyield_12m | D2*yield_12m | D2*Skew_6m |
| D2*Kurt_6m | D2*Kurt_12m | D2*Std_9m | D2*USyield_60m | D2*yield_60m | D2*Kurt_6m |

| | | | | | |
|---|---|---|---|---|---|
| D2*Std_9m | D2*USyield_3m | D2*Skew_9m | D2*USyield_120m | D2*yield_120m | D2*Std_9m |
| D2*Kurt_9m | D2*USyield_12m | D2*Kurt_9m | D2*Yield_3m | D3*Std_1wk | D2*Skew_9m |
| D2*Std_12m | D2*USyield_60m | D2*Std_12m | D2*Yield_12m | D3*Skew_1wk | D2*Kurt_9m |
| D2*Skew_12m | D2*USyield_120m | D2*Skew_12m | D2*Yield_60m | D3*Kurt_1wk | D2*Std_12m |
| D2*Kurt_12m | D2*Yield_3m | D2*Kurt_12m | D2*Yield_120m | D3*Std_1m | D2*Skew_12m |
| D2*USyield_3m | D2*Yield_12m | D2*USyield_3m | D3*Std_1m | D3*Skew_1m | D2*Kurt_12m |
| D2*USyield_12m | D2*Yield_60m | D2*USyield_12m | D3*Skew_1m | D3*Kurt_1m | D2*USyield_3m |
| D2*USyield_60m | D2*Yield_120m | D2*USyield_60m | D3*Kurt_1m | D3*Std_2m | D2*USyield_12m |
| D2*USyield_120m | D3*Std_1wk | D2*USyield_120m | D3*Std_2m | D3*Skew_2m | D2*USyield_60m |
| D2*Yield_3m | D3*Skew_1wk | D2*Yield_3m | D3*Skew_2m | D3*Kurt_2m | D2*USyield_120m |
| D2*Yield_12m | D3*Kurt_1wk | D2*Yield_12m | D3*Kurt_2m | D3*Std_3m | D2*Yield_3m |
| D2*Yield_60m | D3*Std_1m | D2*Yield_60m | D3*Std_3m | D3*Skew_3m | D2*Yield_12m |
| D2*Yield_120m | D3*Skew_1m | D2*Yield_120m | D3*Skew_3m | D3*Kurt_3m | D2*Yield_60m |
| D3*Std_1wk | D3*Kurt_1m | D3*Std_1wk | D3*Kurt_3m | D3*Std_6m | D2*Yield_120m |
| D3*Skew_1wk | D3*Std_2m | D3*Skew_1wk | D3*Skew_6m | D3*Skew_6m | D3*Std_1wk |
| D3*Kurt_1wk | D3*Skew_2m | D3*Kurt_1wk | D3*Kurt_6m | D3*Kurt_6m | D3*Skew_1wk |
| D3*Std_1m | D3*Kurt_2m | D3*Std_1m | D3*Skew_9m | D3*Std_9m | D3*Kurt_1wk |
| D3*Skew_1m | D3*Std_3m | D3*Skew_1m | D3*Kurt_9m | D3*Skew_9m | D3*Std_1m |
| D3*Kurt_1m | D3*Skew_3m | D3*Kurt_1m | D3*Std_12m | D3*Kurt_9m | D3*Skew_1m |
| D3*Std_2m | D3*Kurt_3m | D3*Std_2m | D3*Skew_12m | D3*USyield_3m | D3*Kurt_1m |
| D3*Skew_2m | D3*Std_6m | D3*Skew_2m | D3*Kurt_12m | D3*USyield_12m | D3*Std_2m |
| D3*Kurt_2m | D3*Skew_6m | D3*Kurt_2m | D3*USyield_3m | D3*USyield_60m | D3*Skew_2m |
| D3*Std_3m | D3*Kurt_6m | D3*Std_3m | D3*USyield_12m | D3*USyield_120m | D3*Kurt_2m |
| D3*Skew_3m | D3*Std_9m | D3*Skew_3m | D3*USyield_60m | D3*yield_3m | D3*Std_3m |
| D3*Kurt_3m | D3*Skew_9m | D3*Kurt_3m | D3*USyield_120m | D3*yield_12m | D3*Skew_3m |
| D3*Std_6m | D3*Kurt_9m | D3*Std_6m | D3*Yield_3m | D3*yield_60m | D3*Kurt_3m |
| D3*Skew_6m | D3*Kurt_12m | D3*Skew_6m | D3*Yield_12m | D3*yield_120m | D3*Std_6m |
| D3*Kurt_6m | D3*USyield_3m | D3*Kurt_6m | D3*Yield_60m | | D3*Skew_6m |
| D3*Std_9m | D3*USyield_12m | D3*Std_9m | D3*Yield_120m | | D3*Kurt_6m |
| D3*Skew_9m | D3*USyield_60m | D3*Skew_9m | | | D3*Std_9m |
| D3*Kurt_9m | D3*USyield_120m | D3*Kurt_9m | | | D3*Skew_9m |
| D3*Std_12m | D3*Yield_3m | D3*Std_12m | | | D3*Kurt_9m |
| D3*Skew_12m | D3*Yield_12m | D3*Skew_12m | | | D3*Std_12m |
| D3*Kurt_12m | D3*Yield_60m | D3*Kurt_12m | | | D3*Skew_12m |
| D3*USyield_3m | D3*Yield_120m | D3*USyield_3m | | | D3*Kurt_12m |
| D3*USyield_12m | | D3*USyield_12m | | | D3*USyield_3m |
| D3*USyield_60m | | D3*USyield_60m | | | D3*USyield_12m |
| D3*USyield_120m | | D3*USyield_120m | | | D3*USyield_60m |
| D3*Yield_3m | | D3*Yield_3m | | | D3*USyield_120m |
| D3*Yield_12m | | D3*Yield_12m | | | D3*Yield_3m |

| | | |
|---|---|---|
| D3*Yield_60m | D3*Yield_60m | D3*Yield_12m |
| D3*Yield_120m | D3*Yield_120m | D3*Yield_60m |

**Table 1.5: Monthly Currency Returns Regressions Summary (sampling 1st day of month)**
"UIP", "High Moment", and "Term Structure" represent regressions (1.17a), (1.17b), and (1.17c), respectively. "Obs" is the number of observations. Adj-R2 is adjusted R-squared. P (F-stat) is the overall significance of the regression.

| | UIP | High Moment | Term Structure |
|---|---|---|---|
| **AUDUSD** | | | |
| Obs | 150 | 150 | 150 |
| Adj-R2 | 0.0632 | 0.1629 | 0.2702 |
| P (F-stat) | 0.02 | 0.00 | 0.00 |
| Break Dates | 2002-12-02, 2004-11-01, 2008-11-03 | 2001-11-01, 2005-02-01, 2009-02-02 | 2002-02-01, 2008-07-01, 2010-05-03 |
| **EURUSD** | | | |
| Obs | 142 | 142 | 142 |
| Adj-R2 | -0.0034 | -0.0062 | 0.1222 |
| P (F-stat) | 0.49 | 0.52 | 0.03 |
| Break Dates | 2004-12-01, 2006-09-01, 2008-06-02 | 2004-12-01, 2008-10-01, 2010-08-02 | 2002-11-01, 2004-12-01, 2008-08-01 |
| **GBPUSD** | | | |
| Obs | 149 | 149 | 149 |
| Adj-R2 | 0.0726 | 0.1315 | 0.2596 |
| P (F-stat) | 0.01 | 0.01 | 0.00 |
| Break Dates | 2005-04-01, 2007-04-02, 2009-02-02 | 2002-03-01, 2004-02-02, 2009-04-01 | 2002-01-02, 2008-07-01, 2010-07-01 |
| **NZDUSD** | | | |
| Obs | 105 | 105 | 105 |
| Adj-R2 | 0.1797 | 0.2637 | 0.4168 |
| P (F-stat) | 0.00 | 0.00 | 0.00 |
| Break Dates | 2006-06-01, 2008-09-02, 2009-12-01 | 2008-02-01, 2009-05-01, 2010-09-01 | 2005-11-01, 2008-05-01, 2009-08-03 |
| **USDCAD** | | | |
| Obs | 150 | 150 | 150 |
| Adj-R2 | 0.0163 | 0.0831 | 0.2726 |
| P (F-stat) | 0.23 | 0.04 | 0.00 |
| Break Dates | 2002-12-02, 2004-11-01, 2009-02-02 | 2003-06-02, 2006-10-02, 2008-11-03 | 2004-07-02, 2008-07-02, 2010-06-01 |
| **USDJPY** | | | |

| | | | |
|---|---|---|---|
| Obs | 149 | 149 | 149 |
| Adj-R2 | 0.0382 | 0.1015 | 0.1772 |
| P (F-stat) | 0.08 | 0.02 | 0.00 |
| Break Dates | 2002-01-04, 2004-11-01, 2008-08-01 | 2002-03-01, 2004-04-01, 2009-01-05 | 2002-04-01, 2008-08-01, 2010-07-01 |

**Table 1.6: Correlation between Implied Moments and Short Cuts**

| | 1WK | 1M | 2M | 3M | 6M | 9M | 12M |
|---|---|---|---|---|---|---|---|
| **AUDUSD** | | | | | | | |
| Std with ATM | 0.99 | 0.99 | 0.99 | 0.98 | 0.96 | 0.94 | 0.92 |
| Skew with RR | 0.79 | 0.76 | 0.69 | 0.61 | 0.31 | 0.03 | -0.15 |
| Kurt with BF | 0.52 | 0.19 | 0.10 | 0.02 | -0.20 | -0.35 | -0.43 |
| Obs | 3451 | 3463 | 3433 | 3466 | 3433 | 3433 | 3466 |
| **EURUSD** | | | | | | | |
| Std with ATM | 0.99 | 0.99 | 0.98 | 0.98 | 0.95 | 0.93 | 0.91 |
| Skew with RR | 0.94 | 0.90 | 0.81 | 0.72 | 0.48 | 0.31 | 0.19 |
| Kurt with BF | 0.47 | 0.27 | 0.17 | 0.08 | -0.06 | -0.18 | -0.25 |
| Obs | 3464 | 3297 | 3446 | 3472 | 3446 | 3446 | 3472 |
| **GBPUSD** | | | | | | | |
| Std with ATM | 0.99 | 0.99 | 0.97 | 0.96 | 0.93 | 0.90 | 0.86 |
| Skew with RR | 0.83 | 0.72 | 0.55 | 0.43 | 0.16 | -0.03 | -0.15 |
| Kurt with BF | 0.53 | 0.58 | 0.55 | 0.47 | 0.21 | -0.02 | -0.16 |
| Obs | 3453 | 3465 | 3435 | 3468 | 3435 | 3435 | 3468 |
| **NZDUSD** | | | | | | | |
| Std with ATM | | 0.98 | 0.96 | 0.94 | 0.89 | 0.85 | 0.82 |
| Skew with RR | | 0.78 | 0.67 | 0.58 | 0.45 | 0.34 | 0.21 |
| Kurt with BF | | 0.48 | 0.48 | 0.46 | 0.38 | 0.26 | 0.09 |
| Obs | | 2506 | 2479 | 2508 | 2479 | 2479 | 2508 |
| **USDCAD** | | | | | | | |
| Std with ATM | 1.00 | 1.00 | 1.00 | 1.00 | 0.99 | 0.99 | 0.98 |
| Skew with RR | 0.87 | 0.84 | 0.79 | 0.76 | 0.64 | 0.48 | 0.27 |
| Kurt with BF | 0.40 | 0.03 | -0.08 | -0.12 | -0.17 | -0.19 | -0.15 |
| Obs | 3453 | 3465 | 3416 | 3427 | 3328 | 3262 | 3229 |
| **USDJPY** | | | | | | | |
| Std with ATM | 0.99 | 0.99 | 0.98 | 0.97 | 0.91 | 0.83 | 0.75 |
| Skew with RR | 0.83 | 0.77 | 0.75 | 0.74 | 0.75 | 0.79 | 0.84 |
| Kurt with BF | 0.31 | 0.23 | 0.25 | 0.26 | 0.28 | 0.30 | 0.31 |
| Obs | 3465 | 3468 | 3447 | 3471 | 3447 | 3447 | 3471 |

# Chapter 2. THE TERM STRUCTURE OF RISK IN CURRENCY MARKETS: DYNAMICS, TRADING RULES, AND COMMON RISK FACTORS

## 2.1 INTRODUCTION

This paper studies the empirical performance of currency risks at different horizons and has three main findings contributing to the empirical international finance literature with new empirical findings of the dynamics of currency risk term structure, profitable trading strategies, and common risk factors to understand currency excess returns.

The FX market is the second largest derivatives sector in the over-the-counter market after interest rates, with high liquidity and trading volume. According to the BIS Triennial Survey 2016, FX derivatives trading averaged $5.1 trillion daily. Unlike the equity market that has a benchmark risk index measurement VIX, there is not a uniform way, yet, to measure risk in the FX market. Many studies utilize surveyed forecasts or standard measures of risk, for example, from consumption growth or stock market returns (Engel, 1996; Bacchetta and Wincoop, 2006; Burnside et al., 2006 and 2010). Menkhoff et al. (2012) proposed global FX volatility by averaging absolute daily log returns across all currencies. CBOE announced three new volatility indexes for the FX market using future options prices of CME Dollar/Euro, Dollar/British Pound, and Dollar/Japanese Yen. Besides volatility, skewness is another popular proxy for risk in the FX markets (Jurek, 2014; Brunnermeier et al., 2008). My chapter 1 derived FX option-implied moments of volatility, skewness, and kurtosis together to capture FX risk. In this paper, I propose to use the corridor method by Andersen et al. (2015) for measuring volatility risk in the equity market and accommodate its application in the FX market to extract a forward-looking volatility measure called "FCX", a VIX-like measure for currency markets. I construct daily FCXs for six currency pairs of AUDUSD, GBPUSD, EURUSD, NZDUSD, USDCAD, and USDJPY, and for seven maturities from one week to one year, using FX options pricing data. This new FX risk index is a useful tool to investigate the risk term structure in the FX markets, construct trading strategies, and explain currency excess returns.

First, I find that currency risk at a short horizon (1 week) and the risk at a long horizon (1 year) empirically behave differently during different time regimes. To study this term structure of currency risk and dynamics, I measure its shape using level and slope factors, following the yield curve literature (Nelson and Siegel, 1987). I find that before the 2008 financial crisis, currency risks at different horizons behave similarly, forming a relatively flat shape of the currency risk term structure at a low level. During the 2008 financial crisis, currency risks at different horizons all jump high, and the short-term one is higher than the long-term one, forming a steeply downward-sloping shape of the currency risk term structure. After the crisis, currency risk at the short horizon moves back to a low level while the risk at the long horizon stays at a high level, forming an upward-sloping shape of the currency risk term structure.

The risk term structure has been raising attention recently, mostly in equity and fixed-income markets. Recent leading asset pricing models identifying time-varying risk implied an upward-sloping term structure of equity return volatility (Bansal and Ivan, 2013; Gabaix, 2012; Wachter, 2013; Binsbergen and Koijen, 2017; Marfè, 2015). Empirically, however, it is found that short-term dividends have a higher risk premium than long-term ones (van Binsbergen et al., 2012; van Binsbergen et al., 2013). Some progress has been made in modeling to accommodate the empirical performance, by modifying the rare disaster model originally proposed by Gabaix (2012). Hasler and Marfè (2016) accounted for recoveries in modeling and derived that disaster risk is concentrated in the short term in equity markets. Xie (2014) introduced length of disaster in modeling and derived that the negative slope of VIX term structure corresponds to long disasters. In fixed-income markets, short-rate expectations show more volatility than yield volatility at the long-end, when entering a recession (Cieslak and Povala, 2016). Empirical evidence exists, as well, that instead of always being positive or negative, the slope of the term structure of risk premia is pro-cyclical (van Binsbergen et al., 2013). In currency markets, to our knowledge, there is little literature on this topic, and our work is believed to be new. Our finding in the currency market is consistent with these empirical results and modified rare disaster theories in equity and fixed-income markets, enlightening the direction of currency theory modeling in future research.

I next explore how to use the information from the term structure of currency risk. The results are motivated by the empirical findings by my chapter 1 that FX option-implied moments of different maturities help explain exchange rate dynamics. One way to explore this information is to use a trading strategy. For example, Della Corte et al. (2016) discovered a trading strategy using volatility risk premia, motivated by its predictive ability for currency returns. Sager and Taylor (2014) generated a trading rule using the term structure of forward premia, motivated by the findings by Clarida and Taylor (1997) and Clarida et al. (2003) that it helps forecast exchange rate dynamics. I construct portfolios by sorting level or slope of the risk term structure for each currency pair and find profitable trading strategies by longing high-level currency and shorting low-level currency or by longing the highest slope currency and shorting the lowest slope currency, named Level Trade and Slope Trade, respectively. When I look at the annualized performance of six portfolios, both Slope Trade and Level Trade earn higher Sharpe ratios of 0.78 and 0.26, respectively, than Carry Trade of 0.20. In particular, Slope Trade earns the highest excess return of 9.26% with statistical significance at the 5% level, which has a low correlation of 0.07 to the Carry Trade return of 3.54% without significance and is robust to the 2008 crisis period.

Another way to use the information is to explore the risk premia in currency excess returns. The puzzle of currency excess returns has lasted 30 years and can be explained if there exists a time-varying risk premia (Engel, 1984; Fama, 1984). The vast empirical literature has tried to find risk factors, however, with little success (Engel, 1996; Burnside et al., 2010) until recently. Lustig et al. (2011) studied excess returns of Carry Trade portfolios and identified their first two principal components as two risk factors, showing that they can well explain returns variation across currency pairs. This work is regarded as a benchmark, and many scholars continue to work in this direction on this basis (Menkhoff et al., 2012; Rafferty, 2014). I construct global common factors from levels and slopes across currency pairs and investigate their risk factor roles from three perspectives. First, I follow the classic Fama-MacBeth (FMB) approach with Ordinary Least Squares (OLS) estimation and a standard Stochastic Discount Factor (SDF) approach (Cochrane, 2005) with Generalized Methods of Moment (GMM) estimation (Hansen, 1982) to examine our global level and slope factors' ability of explaining the cross-sectional variation of currency excess returns and compare to Lustig et al. (2011). I find that our global level factor significantly and substantially improves the explanatory power in the cross-sectional variance of currency excess returns (across six portfolios, for example) with a high adjusted R-squared of 0.78 (0.44) by FMB (by GMM), compared to the HML factor by Lustig et al. (2011) with an adjusted R-squared of 0.49 (-0.32) by FMB (by GMM).

Next, I use the beta sorting approach, another classic method (Pastor and Stambaugh, 2003; Ang et al., 2006; Lustig et al., 2011; Menkhoff et al., 2012), to justify a priced risk factor and find that sorting by beta exposures to our global level and slope factors generates a significantly large cross-sectional spread in returns. More specifically, portfolio returns are almost monotonically increasing along an increasing beta of level and almost monotonically decreasing along an increasing beta of slope. For level, the spread is 8.78% with a statistical significance of 5% and the Sharpe ratio of 0.75, and the spread for slope is even higher, 10.04%, with a Sharpe ratio of 0.61 when I look at the six portfolios. These results imply that a high level and low slope correspond to certain high risks. It may be the disaster risk, as suggested in our finding that the 2008 financial crisis has a high level and negative slope, risk of disaster duration, proposed by Xie (2014) that downward-sloping VIX corresponds to long disaster, or risk proximity -- how soon the risk is going to happen (Byunghoon, 2017). What risks are behind level and slope factors leave open areas for research.

Finally, I follow the idea of Menkhoff et al. (2012) to look at the covariance between Carry Trade returns and our global risk factors of level and slope, finding that returns of the high interest rate portfolio have a negative covariance to level factor and that returns of the low interest rate portfolio have a negative covariance to slope factor. The evidence above that high level and low slope correspond to high risk implies that high interest rate currency is a risky asset, co-varying negatively to the risk embodied in level and slope risk factors and thus requires a high expected return. This explains why Carry Trade was popular for decades prior to the 2008 financial crisis but failed during the 2008 financial crisis. This explanation is also consistent with the theoretical work by Farhi and Gabaix (2015) that risky countries have high interest rates to compensate for the risk of currency depreciation in potential world disasters.

The paper is structured as follows. Section two will introduce the corridor method, accommodate its application to construct the new risk index for the FX markets, FCX, and examine its properties and performance. Section three will use the FCX tool to derive a currency risk term structure, look into its behavior, and quantify it by measurable features. Sections four and five explore the usage of currency risk term structure by building trading strategies and constructing global risk factors to understand currency excess returns, respectively. Section six concludes the paper and discusses areas for future research.

## 2.2 A New FX Risk Index: FCX

The FX market is the second largest derivatives sector after interest rates with high liquidity and trading volume. According to the BIS Triennial Survey 2016, FX derivatives trading averaged $5.1 trillion daily. However, there is not a uniformed way yet to measure risk in the FX market. This section will introduce the corridor method by Andersen et al. (2015) for a constructing risk index in the equity market, justify and accommodate its application in the FX market to construct the new FX risk index, FCX, and examine its properties and performances.

### 2.2.1 *A Brief Review of the Corridor Method*

The corridor method is based on the model-free option-implied variance, $MFIV$, a popular way for constructing a volatility index (Dupire, 1993; Neuberger, 1994; Carr and Madan, 1998; Ross, 1976; Breeden and Litzenberger, 1978; Banz and Miller, 1978)[25], for example, the VIX in equity markets, from a forward-looking perspective, reflecting market sentiments and beliefs. The basic setup starts from a frictionless and arbitrage-free market with a risky and risk-free asset traded continuously over the period $[0, T]$, $t = 0$ for the current time. Assume that there is a futures contract expiring at $T_F$ written on the asset, $0 < T_F < T$, and a continuum of European options expiring at $T$ written on the futures contract with a full range of strikes $K$. We denote the futures price at $t$ as $F_t$, put and call options prices as $P_t(K) = P(K, T; F_t, t)$ and $C_t(K) = C(K, T; F_t, t)$, $T$ is maturity, and $r$ is the risk-free rate. As shown in equation (2.1) below, $MFIV$ integrates put and call prices over strikes, aggregating market volatility. It uses the put price when there is a low strike and the call price when there is a high strike, that is, out-of-money (OTM) option prices, reflecting the fact that the OTM option is more liquid than the in-the-money option. For convenience, define $M_t(K) = min\,(P_t(K), C_t(K))$, the minimum of put and call at the strike, that is, the price of the current OTM option, implied by put-call parity that $C_t(K) - P_t(K) = F_t(K) - K$.

$$MFIV_t := \frac{2e^{rT}}{T}\left(\int_0^{F_t} \frac{P_t(K)}{K^2} + \int_{F_t}^{\infty} \frac{C_t(K)}{K^2}\right) dK$$

$$= \frac{2e^{rT}}{T}\int_0^{\infty} \frac{M_t(K)}{K^2}\, dK. \quad (2.1)$$

Andersen et al. (2015) proposed a corridor method to approximate for spot volatility, an improved indicator than VIX index, which has large systematic biases, particularly during the period of

[25] Please see Appendix 2A for more details on MFIV.

market stress. The corridor implied variance, $CIV$, is based on the formula of $MFIV$ but with a finite strike range $[B_L,\ B_H]$ for the integration, as shown in equation (2.2) below. Andersen et al. (2015) showed that only the expected return variation within the corridor is priced by $CIV$, and the truncation of the lower and higher bound in integration does not affect the validity of variance contract pricing, even when there is a price jump and discrete trading up to daily frequency.

$$CIV := \frac{2e^{rT}}{T}\int_{B_H}^{B_L}\frac{M_0(K)}{K^2}dK \quad (2.2)$$

Andersen et al. (2015) proposed an explicit and robust model-free truncating rule for the strike range. For each given strike price, they calculate the ratio of the put price to the sum of put and call option prices, as shown in equation (2.3) below.

$$R(K) = \frac{P(K)}{P(K)+C(K)} \quad (2.3)$$

$$K_{0.5} = R^{-1}(0.5) = F \quad (2.4)$$

The ratio only depends on options prices, monotonically increasing from zero to one, as shown in Figure (2.1) and Figure (2.2), and naturally centering on the futures price as focal points, as shown in equation (2.4) above and Figure (2.1). $R(K) = 0.5$ only happens where $P(K) = C(K)$, implying at the money options where put and call prices are the same, and the strike equals the forward price, the mean of the risk-neutral distribution. For a given percentile, $q \in (0, 1)$, define $K_q = R^{-1}(q)$ as the corresponding strike constituting the $q$-th percentile of $R(K)$, which provides a convenient way to trace locations of strikes. If we use a symmetric percentile of $R(K)$

to define the upper and lower bounds of the strike range, the truncating points reflect the relative importance of the left and right tails in pricing, as shown in Figure (2.2).

Andersen et al. (2015) set $B_L = K_{0.03}$ and $B_H = K_{0.97}$ with $r$ as annual risk-free interest rates, $T = \frac{30\ days}{365}$, and derived the annualized volatility index $CX$, as shown in equation (2.5).

$$CIV_t = \frac{2e^{rT}}{T}\int_{K_{0.03}}^{K_{0.97}} \frac{M_t(K)}{K^2} dK$$

$$CX_t = \sqrt{CIV_t} \quad (2.5)$$

2.2.2 *Innovations of Corridor Application in the FX Markets*

The corridor method was proposed for equity markets by Andersen et al. (2015), and I apply it to the FX market with the following comments. 1) The corridor method features a consistent truncating rule to cut off tails to derive a finite strike range, leaving the strike range always centered around the forward rate and reflecting the relative importance of right and left tails for option pricing in an inherently consistent manner. This ability to capture asymmetry information in pricing serves the goal of incorporating both volatility and skewness information into the FX risk index. 2) FX options are over-the-counter data with a daily frequency. The underlying theory of the corridor method, proved by Bondarenko (2014), requires very general conditions, accommodates discrete samples up to daily data, and is robust to price jump. These features make this corridor method favorable for the FX option.

The Black-Scholes formula for pricing FX options is as shown in equations (2.6) below.

$$C_t = e^{-r^f T} S_t \phi(d_1) - e^{-r^d T} K \phi(d_2)]$$

$$P_t = -e^{-r^f T} S_t \phi(-d_1) + e^{-r^d T} K \phi(-d_2)], \quad (2.6)$$

where $\phi(.)$ denotes the standard normal cumulative distribution function, and

$$d_1(K_{25\delta p}) = \frac{\log\left[\frac{S_t}{K_{25\delta p}}\right] + \left(r^d - r^f + 0.5\sigma_{25\delta p}^2\right)T}{\sigma_{25\delta p}\sqrt{T}}, d_2(K_{25\delta p}) = d_1(K_{25\delta p}) - \sigma_{25\delta p}\sqrt{T},$$

$$d_1(K_{25\delta c}) = \frac{\log\left[\frac{S_t}{K_{25\delta c}}\right] + \left(r^d - r^f + 0.5\sigma_{25\delta c}^2\right)T}{\sigma_{25\delta c}\sqrt{T}}, d_2(K_{25\delta c}) = d_1(K_{25\delta c}) - \sigma_{25\delta c}\sqrt{T},$$

$$d_1(K) = \frac{\log\left[\frac{S_t}{K}\right] + (r^d - r^f + 0.5\sigma^2)T}{\sigma\sqrt{T}}, d_2(K) = d_1(K) - \sigma\sqrt{T}, \sigma \approx \sigma_{atm}, \qquad (2.7)$$

where $\sigma_{25\delta p}, \sigma_{ATM}, \sigma_{25\delta c}$ are implied volatility quotes of 25% delta put options, ATM options, and 25% delta call options. $\delta$ denotes delta, the rate of the option price change over the spot price change ($\delta = \frac{\partial C}{\partial S}$). $r^d$ and $r^f$ denote domestic and foreign interest rates, respectively.

To apply the corridor method to FX data, I need to accommodate the differences between equity options and FX options. 1) First, the equity option has directly observed strikes and price, while the FX option quotes delta and implied volatility. Therefore, I need to back out the strikes first according to the definition of delta, as shown in equation (2.8).

$$K_{25\delta p} = S_t e^{[\phi^{-1}(0.25e^{r^f T})\sigma_{25\delta p}\sqrt{T}+(r^d-r^f+0.5\sigma_{25\delta p}^2)T]}$$

$$K_{ATM} = S_t e^{(r^d-r^f+0.5\sigma_{ATM}^2)T}$$

$$K_{25\delta c} = S_t e^{[-\phi^{-1}(0.25e^{r^f T})\sigma_{25\delta c}\sqrt{T}+(r^d-r^f+0.5\sigma_{25\delta c}^2)T]} \quad (2.8)$$

I then calculate option prices following the Black-Scholes model, as shown in equation (2.6) above. 2) Second, unlike the equity option, which has a good number of quotes from a wide range of strikes, FX options have only five discrete quotes given maturity. Interpolation and extrapolation are needed to derive a sufficient strike range following Castagna and Mercurio (2007) and Castagna (2010), which has been a common way to deal with the FX option (Jurek, 2014).[26] This will cause inaccuracy in the tails, which can be cut off by the corridor method. 3) Unlike VIX in the equity market, a single volatility index constructed by one option of the S&P 500, FX options have different underlying assets by currency pair $i$. Thus, in the FX market, each currency pair will have a risk index. 4) The corridor index requires a discounting term $e^{rT}$ for annualizing the number, and the interest rate $r$ is easy to define in the equity market since it only involves a single country. However, each currency pair involves two countries. Here I choose to consistently use US risk-free interest rates $r_{US}$ for the discounting term, following Della Corte et al. (2016). 5) Additionally, VIX has only one maturity of 30 days, but I construct an FX risk index for different maturity for investigating term structure information. Now I can derive the formula for the FX corridor index $FCX$, as shown in equation (2.9).

[26] Please see Appendix 2B for detailed steps of interpolation.

$$FCIV_{t,T}^{i} = \frac{2e^{r_{US,t}^{T}}}{T}\int_{K_{0.03}}^{K_{0.97}} \frac{M_{i,t}(K)}{K^2} dK$$

$$FCX_{t,T}^{i} = \sqrt{FCIV_{t,T}^{i}} \quad (2.9)$$

$$T = \frac{maturity\ days}{365}$$

Empirically, in the discrete world, I use the following method to proxy for integration (Andersen et al., 2015). Suppose that there are $N$ European style OTM options written on an asset price with the same maturity $T$ and strike prices $K_j, j = 1, 2, \ldots N$, with a strike range $(K_L, K_H)$ truncated by the rule $K_{0.03} \ll K_L < K_{L+1} < \ldots < K_f \ll F < K_{f+1} < \ldots < K_H \ll K_{0.97}$. $F$ is the current $t = 0$ forward price for time $T$, and $K_f$ is the first strike price below the forward price, where $2 < f < N - 1$, supported by the reasonable cross-sectional options. With discrete data, the implied variance can be approximately calculated as shown in equation (2.10). Finally, I obtain the forward-looking volatility measure for FX markets, $FCX$.

$$\widehat{FCIV}_{t,T}^{i} = \frac{2e^{r_{US,t}T}}{T}\sum_{j=L}^{H} \frac{\Delta K}{K^2} M_{i,t}(K) - \frac{1}{T}[\frac{F_{i,t}}{K} - 1]^2$$

$$\widehat{FCX}_{t,T}^{i} = \sqrt{\widehat{FCIV}_{t,T}^{i}} \quad (2.10)$$

$$\Delta K_j = \frac{K_{j+1} - K_{j-1}}{2}$$

### 2.2.3 *Properties and Performances of FCX*

This section uses historical data on FX options to examine the empirical performances of FCX, to verify the theoretical and mathematical statements about the innovations of the corridor method in Andersen et al. (2015): through the inherently consistent truncating rule for strike range, the corridor index is able to keep the information 1) always centered around the forward rate and 2) subsuming asymmetric importance of left and right tails of return distribution in pricing.

The spot rates and FX options data are from JP Morgan, covering six currency pairs in the main developed countries, AUDUSD, EURUSD, GBPUSD, NZDUSD, USDCAD, USDJPY, at a daily frequency from 2000 to 2013. The 25% delta options data are used for their high liquidity with seven maturities of one week, one month, two months, three months, six months, nine months, and 12 months. The forward rates and risk-free interest rates (The London Inter-bank Offered Rate, LIBOR rate) are from Datastream, except for NZDUSD of one-week maturity, which are from Bloomberg.

(1) Strike range always centers around a forward price.

I use the forward rate to measure the mean of a risk-neutral return distribution, which is changing dynamically, to investigate how the truncated strike range evolves accordingly. It is found that the truncated strike range always centers around the forward rate no matter how the return distribution is changing across time, as shown in Figure (2.1). This guarantees inter-temporal consistency of the strike range for calculating the risk index.

**Figure 2.1**

(2) Strike range reflects relative importance of right and left tails for option pricing.

I use a risk reversal option to measure the asymmetry of a currency return distribution. Risk reversal, denoted as $rr$, is a combination of longing a call option and shorting a put option at the same strike price and time. A 25% delta risk reversal is defined as $rr_{25\delta} = \sigma_{25\delta c} - \sigma_{25\delta p}$. Thus, a positive risk reversal indicates that the implied volatility of the call option is higher than the one of a put option, implying positive skewness in the return distribution. Therefore, the risk reversal rate is a conventional proxy for skewness in practice (Chen, 1998).

I then calculate the FCX and look at its strike range under the assumptions of a negative, zero, and positive risk reversal rate. It is found that when using symmetric percentiles of the R function to cut off tails, the truncated strike range $[k_L, k_H]$ monotonically moves towards the right, as the risk reversal rate increases from negative to positive, as shown in Figure (2.2). This reflects the relative importance of right and left tails for the variance pricing in an inherently consistent manner.

**Figure 2.2**

(3) FCX compensates for risk of negative skewness.

This section directly examines the relationship between the FCX and risk reversal rate. As shown in Figure (2.3), the FCX, when skewness is negative, is always higher than the FCX when skewness is positive, reflecting its ability to compensate for the risk of negative skewness.

**Figure 2.3**

(4) FCX is able to capture market stress in terms of volatility.

This section evaluates FCX's ability to capture market stress in terms of volatility. A common approach is to compare it with realized volatility (RV), usually approximated by the squared return (Andersen et al., 2015).[27] Since the FCX is an option-implied volatility measure, which is forward-looking, the realized volatility is calculated as the summation of daily squared returns over the future horizon. As shown in Figure (2.4), FCX closely captures realized volatility, particularly on a short horizon, spiking during the 2008 crisis, able to capture market stress well.

**Figure 2.4**

## 2.3 TERM STRUCTURE OF CURRENCY RISK

In this section, I measure the term structure of currency risk using FCXs of seven maturities and find that the level and slope of the term structure information is useful for explaining currency excess returns.

### 2.3.1 *Behavior*

With the tool of FCX to proxy for FX risk comprehensively, I calculate FCXs for different maturities from one week to 12 months to look into the behavior of currency risk term structure. Unlike the yield curve, which has maturities up to ten or twenty years, currency quotes and

[27] Please see more details in Appendix 2C.

volatility measures usually use maturity up to 12 months (Sager and Taylor, 2014; Xie, 2014). Figure (2.5) plots the time series dynamics of the FCX at different maturities for each currency pair. The FCXs of different maturities share common movements. They are all high during the 2008 crisis and all low before the 2008 crisis. However, the ranking of FCX levels at different maturities changes. Short-term FCX is lower than long-term FCX before the 2008 crisis, while short-term FCX is higher during the 2008 crisis. This is consistent with findings by Xu and Taylor (1994), that there is a difference between short-term and long-term volatility expectations. To further investigate the term structure shape of FCX, I look at how FCX behaves across maturities on a given day, as shown in Figure (2.6). Before the 2008 financial crisis, FCXs at different horizons behave similarly, forming a relatively flat term structure at a low level. During the 2008 financial crisis, FCXs at different horizons all jump high, and the short-term FCX is higher than the long-term one, forming a steeply downward-sloping term structure. After the crisis, currency risk at the short horizon moves back to a low level while the risk at the long horizon stays at a high level, forming an upward-sloping term structure. The behavior is consistent across all the currencies. This result is believed to be a new result for the currency markets, and the results are consistent with empirical results in equity and fixed-income markets and their modified theories of rare disasters.

**Figure 2.5**

**Figure 2.6**

### 2.3.2 *Features: Level and Slope*

To measure the term structure shape of currency risk using FCX, I follow the methodology of Nelson-Siegel factors (Nelson and Siegel, 1987) used in the yield curve literature, studying the term structure shape of the interest rate. The Nelson-Siegel factors, level, slope, and curvature, can be extracted from the first three principal components of yield curve data. Level and slope are regarded as the most important, explaining the most variation of yields, and I will focus on these two factors to study currency risk term structure. To gain economic intuition, we approximate the level factor by the short-term rate or the average of all terms' rates, and the slope factor is approximated by the difference between long-term rate and short-term rate. Following this idea, I first perform a principal component analysis on the FCXs of different maturities and find that the first two principal components PC1 and PC2 account for over 99% of FCX variance consistently across all currency pairs, as shown in Table (2.1). The first principal component PC1 has roughly equal loadings on the FCX of each maturity, working as taking an average of all terms' FCXs, implying its role as a level factor, as shown in Table (2.2). The second principal component PC2 has a negative loading on short-term FCXs and positive loading on long-term FCXs, working as taking the difference between long-term and short-term FCXs, implying its role as a slope factor.[28]

**Table 2.1**

**Table 2.2**

**Table 2.3**

[28] Table 2.3 shows the variance-covariance matrix of FCXs of different maturities.

Next, I directly calculate the level by taking the average of FCXs of all maturities and directly calculate the slope by taking the difference between the FCX with a 12-month maturity and a one-week maturity, as shown in equation (2.11) and (2.12).

$$Level_{i,t} = \frac{1}{7}\sum_{T} FCX_{i,t,T}\,, T = 1w, 1m, \ldots, 12m \quad (2.11)$$

$$Slope_{i,t} = FCX_{i,t,12m} - FCX_{i,t,1w} \quad (2.12)$$

I find that they are highly correlated to the first two principal components derived above, consistently across all currency pairs, as shown in Table (2.4). All these findings are consistent with the yield curve literature in fixed-income markets. I follow the literature to use these directly calculated factors with high transparency to measure the shape features of the currency risk term structure. Figure (2.7) shows the time series dynamics of the two features of the currency risk term structure for each currency pair. Before the 2008 crisis, the currency risk term structure has a low level, and the slope moves around zero. During the 2008 crisis, the currency risk term structure has a high level, and the slope is prominently negative. After the 2008 crisis, the currency risk term structure has a medium level and slope moves above zero. I will explore the usage of these informational features in the following sections.

**Table 2.4**

**Figure 2.7**

## 2.4 TRADING STRATEGIES: LEVEL TRADE AND SLOPE TRADE

In this sub-section, I explore trading strategies using the derived features above, the level and slope of currency risk term structure, motivated by the finding of my chapter 1 that it has predictive power in exchange rate dynamics.

### 2.4.1 *Currency Excess Returns and Trading Rules*

Following Della Corte et al. (2012) and Rafferty (2012), I treat the USD as the domestic currency and use $s_{t+1}$ to denote the log spot exchange rate at time $t+1$ and $f_t^{t+1}$ to denote the log forward rate at time $t$ with one-month maturity expiring at $t+1$. The currency excess return is defined as buying foreign currency in the forward market and selling it in the spot market in one month. That is, the excess return is calculated as $r_{t+1} = s_{t+1} - f_t^{t+1}$ if the USD is domestic in the original quote, and $r_{t+1} = f_t^{t+1} - s_{t+1}$ if the USD is foreign in the original quote, following Burnside et al. (2010) who inverted the original quotes when the USD is foreign, thus all returns are expressed in USD. Table (2.5) records details of currency quotes and an excess return definition.

**Table 2.5**

I look at the monthly investment horizon for our main results for its high liquidity by aggregating daily data into monthly using end-of-month observations, following Lustig et al. (2011) and Menkhoff et al. (2012). At the end of each month $t$, I first sort currencies by their levels of the risk term structure. Due to the small number of currency pairs, to generate a relatively wider cross-sectional sample, I construct six portfolios for our main results with a single currency pair in each portfolio by putting the lowest 17% level currency into the first portfolio (I1) and putting the highest 17% level currency into the last portfolio (I6). I also report results of three portfolios with two currency pairs in each portfolio to relieve the concern of noise in individual assets by putting the lowest 33% level currencies into the first portfolio (P1) and putting the highest 33% level currencies into the last portfolio (P3). Portfolios are rebalanced at the end of each month $t$. Within each portfolio, I average the excess return across currencies, multiply the mean by 12 to annualize the return, multiply the standard deviation by $\sqrt{12}$ to annualize the value and calculate the annualized Sharpe ratio using the annualized return and the annualized standard deviation, following Lustig et al. (2011). I find that the excess return almost monotonically increases as the level increases, as shown in Table (2.6) Panel a. Naturally, I come up with the Level Trade strategy by longing the last portfolio of the highest level of FX risk term structure and shorting the first portfolio of the lowest level. I repeat the above steps to construct a Slope Trade portfolio by sorting the slope of each currency and find profit by longing the last portfolio of the highest slope and shorting the first portfolio of the lowest slope. These trading strategies consistently generate positive returns with good Sharpe ratios all above 0.2. The positive return of the Slope Trade 6 portfolios gains statistical significance at the 5% level with a high Sharpe ratio of 0.59. In addition, the skewness of each portfolio return generally increases, from shorting the portfolio of low level or slope to longing the portfolio of high level or slope.

**Table 2.6**

### 2.4.2 *Comparison to Carry Trade*

There is a popular trading strategy in the currency literature, Carry Trade, which earns a profit by longing the currency of the highest interest rate and shorting the currency of the lowest interest rate. To compare the performances of our trading strategies to Carry Trade, I first construct Carry Trade portfolios using the same data samples. I repeat the above steps, sorting by the interest rate differential for each currency and derive the return by longing the portfolio of the highest interest rate currencies and shorting the portfolio of the lowest interest rate currencies. I directly sort on the interest rate differential with the US rate as a base for straightforwardness, and the results are summarized in Table (2.7). Due to a small number of currency pairs and a short time period in our data sample, I also report the summarized results of sampling on the 1st day or middle day of each month and summarized results of weekly investment horizon to compare with Carry Trade, as shown in Table (2.9).

As shown in Table (2.7), Carry Trade generates positive returns, which are consistent with the literature (Lustig et al., 2011; Menkhoff, 2012; Rafferty, 2012; Della Corte et al., 2016). The return did not show statistical significance, which is consistent with Della Corte et al. (2016) whose sample period is closest to our data sample, all admittedly short and including the 2008 financial crisis. The return around 3.5% and Sharpe ratio between 0.2 and 0.3 are slightly lower than Della Corte et al. (2016) who has more currency pairs, but this issue is relieved when I sample 1st day or middle day observations of each month, as shown in Table (2.9) Panel a and b.

**Table 2.7**

**Table 2.8**

**Table 2.9**

Table (2.8) summarizes and compares performances of Level Trade, Slope Trade, and Carry Trade. Of the six portfolios, Slope Trade earns the highest excess return of 7.24% with a statistical significance at the 5% level and earns the highest Sharpe ratio of 0.59. Level Trade and Carry Trade both earn insignificant positive excess returns of 2.99% and 3.54%, respectively, but Level Trade earns a higher Sharpe ratio of 0.26 than Carry Trade of 0.20. With the three portfolios, all strategies' returns are insignificant, with Level Trade and Carry Trade earning a Sharpe ratio of 0.28 and 0.29, respectively, both better than the Slope Trade. Furthermore, the skewness of Level and Slope Trades are both always higher than that of Carry Trade. In addition, I notice that the correlation between the Slope Trade return and Carry Trade return is very low, while the Level Trade return is highly correlated to the Carry Trade return. This motivates us to explore their differences further in the next section 2.4.3. When sampling the 1st day or middle day of each month or when looking at a weekly investment horizon, returns all go up for these strategies, but rankings maintain quite consistent, with the Slope Trade earning more statistical significance, as shown in Table (2.9).

### 2.4.3 *Performance by Time Regime*

In section 2.3, both the level and slope perform differently in different time regimes. This is consistent with my chapter 1 that detected structural breaks when using the FX option-implied moments of different maturities to explain currency returns. Thus, I look further into these trading strategies' performance before, during, and after the crisis, respectively, following Della Corte et al. (2016) who performed the same test using recession periods defined by the National Bureau of Economic Research (NBER), December 2007 to June 2009. As shown in Table (2.10) Panel c, Carry Trade works during non-crisis periods, earning an excess return of 9.03% (5.56%) with a Sharpe ratio of 0.70 (0.60) with six portfolios (three portfolios) before the 2008 crisis, similar to its performance after the crisis, earning an excess return of 8.46% (7.72%) with a Sharpe ratio of 0.52 (0.67) with six portfolios (three portfolios), though all insignificant but much better than its performance during the 2008 crisis when it earns a negative return. This is consistent with the well-recorded fact that Carry Trade works well before the crisis but fails during the 2008 crisis (Menkhoff et al., 2012; Della Corte et al. 2016). In this sense, Level Trade has the similarity that it also fails during the 2008 crisis, earning a negative return. The difference comes from the fact that its performance before and after the 2008 crisis differs a lot. Level Trade earns a highly positive excess return of 8.26% (12.19% with significance at the 5% level) with a Sharpe ratio of 0.80 (1.18) with six portfolios (three portfolios) while it earns a low return before the crisis, as shown in Table (2.10) Panel a. In contrary, when I look at six portfolios, the Slope Trade always earns a positive returns with Sharpe ratios above 0.35, consistently across all these different time regimes, and more importantly, earns its highest excess return of 19.45% with a Sharpe ratio of 1.45 during the 2008 crisis, as shown in Table (2.10) Panel b, though the Slope Trade does not have a strong performance in three portfolios. These similarities and differences in patterns of performance by regime may explain the high and low correlations between these trading strategies found in section 2.4.2.

**Table 2.10**

## 2.5 Global Risk Factors: Global Level and Slope

There is a strand of literature seeking global risk factors to explain risk premia in currency excess returns (Lustig et al., 2011; Menkhoff et al., 2012; Rafferty, 2014). In section 2.3, I already noticed that these risk term structures of different currency pairs share common features and common dynamics. This further motivates us to construct common global risk factors to explain cross-sectional variation in currency risk premia.

### 2.5.1 *Construct Global Risk Factors*

I aggregate levels and slopes of each currency's risk term structure by straightforwardly taking their average to derive common global risk factors, as shown in equations (2.13) and (2.14), following Della Corte et al. (2016), Menkhoff et al. (2012), and Rafferty (2012) who averaged for aggregation as well to construct their global risk factor.

$$GlobalLevel_t = \frac{1}{6}\sum_i Level_{i,t}\, , i = AUDUSD, \ldots, USDJPY \quad (2.13)$$

$$GlobalSlope_t = \frac{1}{6}\sum_i Slope_{i,t}\, , i = AUDUSD, \ldots, USDJPY \quad (2.14)$$

As shown in Figure (2.8), global factors capture common dynamics of risk term structure of different currency pairs well, with level peaking and slope dipping during the 2008 crisis.

**Figure 2.8**

I also performed a principal component analysis to extract common factors across currency pairs for comparison.[29] For levels and slopes, I extracted their first principal component, respectively, named PC_level and PC_slope. Almost equal loadings on each currency pair, as shown in Table (2.12), imply that the principal components work essentially as the role of an average. As shown

[29] Table (2.11) summarizes the variance-covariance matrix of risk factors across different currencies.

in Table (2.13), they are indeed highly correlated with the average calculated above, both accounting for a high proportion of the variance of 93.7% and 85.59%, respectively, further justifying our choice of taking the average to construct global common risk factors.

**Table 2.11**

**Table 2.12**

**Table 2.13**

### 2.5.2 *Explain Currency Excess Returns: Comparison to Lustig et al. (2011)*

With the global risk factors extracted from the information in the currency risk term structure, this section investigates their abilities to explain currency risk premia, looking at the Carry Trade portfolios sorted by interest rate, a classic example in the currency literature (Lustig et al., 2011; Menkhoff et al., 2012; Rafferty, 2012; Della Corte et al., 2016). I compare our results to Lustig et al. (2011), a benchmark in recent years. Lustig et al. (2011) proposed two risk factors from Carry Trade portfolios returns, dollar risk factor $DOL_t$ calculated as the average currency excess return of all the portfolios, and carry factor $HML_t$, calculated as the difference between the highest interest rate portfolio return and lowest interest rate portfolio return, as shown in equation (2.15) and (2.16).

$$DOL_t = \frac{1}{P}\sum_{p=1}^{P} r_{p,t} \quad (2.15)$$

$$HML_t = r_{P,t} - r_{1,t} \quad (2.16)$$

$$P: number\ of\ carry\ trade\ portfolios$$

$DOL_t$ can be interpreted as the aggregate currency market returns relative to the USD, playing a role like market return in CAPM (Lustig et al., 2011; Rafferty, 2012). $DOL_t$ is regarded as a benchmark risk factor in the currency market, and people continue the research on its basis (Lustig et al., 2011; Menkhoff et al., 2012; Rafferty, 2012).

This section compares the explanatory power of our risk factors and Lustig's factor in currency excess returns by performing both a time-series test (Fama and MacBeth, 1973; Fama and French; 1993; Della Corte et al., 2016) and a cross-sectional test (Fama and MacBeth, 1973; Cochrane, 2005; Lustig et al., 2011; Menkhoff et al., 2012). Using our data sample, I find that the level factor substantially improves explanatory power in the cross-sectional variance of currency excess returns.

(1) Time series test

I first utilize the time-series approach by Fama and French (1993) who justified adding two new factors besides the market in equity markets, which are used by Della Corte et al. (2016) in the currency market as well. I regress monthly excess returns of each Carry Trade portfolio sorted by interest rate $r_{p,t}$ on risk factor candidates $f_t$ by Lustig et al. (2011) and by our paper, respectively, as shown in equation (2.17). The coefficients $\beta_p$ are factor loadings, implying a sensitivity of those excess returns to the factors. The factor loadings and the R-squared value of the regression are indicators of how much the time-series variation in returns can be explained by the time series variation in risk factors, and the intercept $\alpha_p$ is the pricing error measuring how wrong the overall the model is (Fama and French, 1993; Della Corte et al., 2016).

$$r_{p,t} = \alpha_p + \beta_p f_t + \epsilon_{p,t} \quad (2.17)$$

I first do the time series test, regressing Carry Trade portfolios returns on HML factors by Lustig et al. (2011), as shown in equation (2.18) below and find consistency with their results.

$$r_{p,t} = \alpha_p + \beta_{p,dol} DOL_t + \beta_{p,hml} HML_t + \epsilon_{p,t} \quad (2.18)$$

Both of us have DOL betas $\beta_{p,dol}$ with all positive signs and roughly equal size, HML betas $\beta_{p,hml}$ are negative in the low interest rate portfolio and positive in the high interest rate portfolio, a high adjusted R-squared, and pricing errors $\alpha_p$ of some statistical significance, as shown in Table (2.14) Panel a. Next, I calculate time series tests on our risk factors level and slope, as shown in equation (2.19) and (2.20) below and compare them to the HML results.

$$r_{p,t} = \alpha_p + \beta_{p,dol} DOL_t + \beta_{p,level} Level_t + \epsilon_{p,t} \quad (2.19)$$

$$r_{p,t} = \alpha_p + \beta_{p,dol} DOL_t + \beta_{p,slope} Slope_t + \epsilon_{p,t} \quad (2.20)$$

Level and slope did not show consistent improvement in explanatory power in terms of adjusted R-squared or beta significance, but they do perform better in further weakening the statistical significance of the pricing error. As shown in Table (2.14) Panel b and c, the significance of the pricing error disappears completely when using the level factor and mostly when using the slope factor. In addition, I find that the slope factor has a negative beta in the low interest rate portfolio and a positive beta in the high interest rate portfolio, like HML, showing its potential to explain excess returns across portfolios.

**Table 2.14**

(2) Cross-sectional tests

Next, I perform cross-sectional tests using two approaches. One is the traditional two-stage Fama-MacBeth (FMB) approach by Fama and MacBeth (1973) with Ordinary Least Squares (OLS) estimation. The first stage is to run a time-series test as shown above in equation (2.17), regressing monthly excess return of each portfolio $r_{p,t}$, on the risk factor $f$ to derive exposure of each portfolio $\beta_p$. The second stage is to run a cross-section test, as shown in equation (2.21) below, regressing the average excess return of each portfolio $r_p$ on its estimated exposure $\widehat{\beta_p}$ derived from equation (2.17) to find the price of the risk factor $\lambda$. That is, I investigate the variation in factor exposures to explain the variation in average returns across portfolios. I do not include a constant in the second stage regression, following Lustig et al. (2011) and Menkhoff et al. (2012).

$$r_p = \widehat{\beta_p}\lambda + \epsilon_p \quad (2.21)$$

I also consider the Stochastic Discount Factor (SDF) approach by Cochrane (2005). Asset pricing theory suggests that there is a stochastic discount factor $m_t$, pricing the excess return $r_{p,t}$. With no arbitrage, the excess return should have a zero expected price if adjusted by risk, as implied by the Euler equation (2.22). I assume that the SDF has a linear form of risk factors $f_t$, as shown in equation (2.23) below, where $\mu$ is mean of factors, and $b$ is a vector of factor loadings.

$$E[m_t r_{p,t}] = 0 \quad (2.22)$$

$$m_t = 1 - b'(f_t - \mu) \quad (2.23)$$

Combining equation (2.22) and (2.23) derives the moment conditions, as shown in equation (2.24), and I use the Generalized Method of Moments (GMM) approach by Hansen (1982) to estimate parameters $\mu$ and $b$.

$$E[(1 - b'(f_t - \mu))r_{p,t}] = 0 \ (2.24)$$

This linear factor model implies a beta pricing model, that the expected excess return of a portfolio equals the risk factor price $\lambda$ times risk quantities $\beta_p$ of the portfolio. The relation between price $\lambda$ and the parameter $b$ in equation (2.24) is given by equation (2.26), where $\Omega_f$ is the variance-covariance matrix of risk factors $f_t$. In this way, I can back out the price of the risk factor, $\lambda$.

$$E[r_p] = \lambda'\beta_p \quad (2.25)$$

$$\lambda = \Omega_f b \quad (2.26)$$

To obtain the standard error of λ, I use the Delta method. To obtain adjusted R-squared, I follow steps in Rafferty (2012) to look at how much variance of the actual value $r_p$ on the average is explained by the estimated value $\widehat{r_p}$, which is calculated as equation (2.27), where $\Omega_{f,r}$ is the variance-covariance matrix of risk factors $f_t$ and excess returns $r_{p,t}$.

$$\widehat{r_p} = \Omega_{f,r} b \quad (2.27)$$

I first do these cross-sectional tests on HML factors by Lustig et al. (2011), applying equations (2.28) and (2.29) below to the data sample in my paper, and record the results in Table (2.15) Panel a.

$$\text{FMB: } r_p = \widehat{\beta_{p,dol}} \lambda_{dol} + \widehat{\beta_{p,hml}} \lambda_{hml} + \epsilon_p \quad (2.28)$$

$$\text{GMM: } E[(1 - b_{dol}(DOL_t - \mu_{dol}) - b_{hml}(HML_t - \mu_{hml}))r_{p,t}] = 0, \lambda = \Omega_{DOL,HML} b \quad (2.29)$$

Table (2.16) records the performance of HML factors in literature, by Lustig et al. (2011) and Della Corte et al. (2016). As it shows, my replication results are overall consistent with theirs. Both of us have a positive adjusted R-squared by the FMB approach though our value is lower due to fewer currency pairs, 0.49 (0.11) in six portfolios (three portfolios). Both of us have a negative adjusted R-squared by GMM estimation and positive prices of DOL and HML factors with close values around 140-323 basis points and 173-393 basis points per annum, respectively. Next, I perform cross-sectional tests on our level factor (following equations (2.30) and (2.31)) and slope factor (following equation (2.32) and (2.33)), respectively.

$$\text{FMB: } r_p = \widehat{\beta_{p,dol}} \lambda_{dol} + \widehat{\beta_{p,level}} \lambda_{level} + \epsilon_p \quad (2.30)$$

$$\text{GMM: } E[(1 - b_{dol}(DOL_t - \mu_{dol}) - b_{hml}(Level_t - \mu_{hml}))r_{p,t}] = 0, \lambda = \Omega_{DOL,Level} b \quad (2.31)$$

$$\text{FMB: } r_p = \alpha + \widehat{\beta_{p,dol}} \lambda_{dol} + \widehat{\beta_{p,slope}} \lambda_{slope} + \epsilon_p \quad (2.32)$$

$$\text{GMM: } E[(1 - b_{dol}(DOL_t - \mu_{dol}) - b_{slope}(Slope_t - \mu_{slope}))r_{p,t}] = 0, \lambda = \Omega_{DOL,Slope} b \quad (2.33)$$

In comparison, the level factor has a consistently positive adjusted R-squared of 0.78 (0.21) by the FMB approach and 0.44 (0.67) by the GMM approach in six portfolios (three portfolios), substantially improving the cross-sectional explanatory power of currency excess returns, as shown in Table (2.15) Panel b. In addition, using the level factor gains not only statistical significance in its own price estimation of 185-404 basis points per annum but also brings statistical significance to the DOL factor price estimation. The slope factor did not show consistent improvement in the cross-sectional explanatory power, and its price estimation sometimes goes negative, as shown in Table (2.15) Panel c, which I will explore further in the next section.

**Table 2.15**

**Table 2.16**

### 2.5.3 *Beta Sorting*

Another popular approach to examine risk premia is beta sorting (Ang et al., 2006; Pastor and Stambaugh, 2003), adopted by Lustig et al. (2011) and Menkhoff et al. (2012) in the FX field as well. I run rolling time-series regressions, regressing the excess return of each currency on our risk factor level or slope in a rolling window of 36 months to derive time-varying betas, the exposures to the risk factor. Then, at the end of each month, I group currencies into portfolios by sorting their betas, allocating currencies with the lowest beta to the first portfolio and currencies with highest the beta to the last portfolio. Then, I compute the average excess return of each portfolio, finding it almost monotonically increasing along the increasing beta of the level and almost monotonically decreasing along the increasing beta of the slope. As shown in Table (2.17) Panel a, for level, the spread by longing the last portfolio of the highest beta and shorting the first portfolio of the lowest beta is as high as 16.07% (14.28%), with statistical significance at a 1% (0.1%) level and a Sharpe ratio exceeding one of 1.14 (1.34) when I look at six portfolios (three portfolios). As shown in Table (2.17) Panel b, for slope, the spread by shorting the last portfolio of the highest beta and longing the first portfolio of the lowest beta, is even higher, 18.82% (14.36%) with statistical significance at a 1% (0.1%) level, earning an even higher Sharpe ratio of 1.19 (1.42), when I look at six portfolios (three portfolios). I repeat the beta sorting analysis using a 12-month window to estimate beta and obtain a spread of 16.07% (14.28%) for level, with a statistical significance at the 1% (0.1%) level and a Sharpe ratio exceeding one of 1.14 (1.34), when I look at six portfolios (three portfolios). For slope, with a statistical significance at the 1% (0.1%) level, I obtain a Sharpe ratio exceeding one of 1.14 (1.34) when I look at six portfolios (three portfolios), as shown in Table (2.18).

**Table 2.17**

**Table 2.18**

The significant cross-sectional spread in returns further justifies that our proposed risk factors are priced. Following the logic of Lustig et al. (2011), for level, high beta asset loads more on the level factor and earns a high risk premium, which is consistent with the results of the positive price of level risk in section 2.5.2. For slope, low beta asset loads less on the slope factor but earns a high risk premium, suggesting a negative price of slope risk. These results suggest that the high level and low slope correspond to certain high risk. The risk may be disaster risk, as suggested in sections 2.3 and 2.5.1, that the 2008 financial crisis has a high level and negative slope. It may be the risk of disaster duration, proposed by Xie (2014), that the downward-sloping VIX corresponds to long disaster, or it may be the risk proximity, how soon the risk is going to happen (Byunghoon, 2017). What risks are behind the level and slope factors leave open areas for research.

### 2.5.4 *A Time Series Perspective to Explain Carry Trade*

At last, I follow the idea of Menkhoff et al. (2012) to examine the time-series relationship between Carry Trade returns and our global risk factors of level and slope. I use the Carry Trade portfolios constructed in section 2.4.2, sorted by their interest rate from low to high, then regress the excess return of each portfolio $r_{p,t}$ on our global risk factors level and slope to derive the parameters $\beta_{p,level}$ and $\beta_{p,slope}$, respectively, as shown in equations (2.34) and (2.35).

$$r_{p,t} = \alpha_p + \beta_{p,level} Level_t + \epsilon_{p,t} \quad (2.34)$$

$$r_{p,t} = \alpha_p + \beta_{p,slope} Slope_t + \epsilon_{p,t} \quad (2.35)$$

These parameters can be interpreted as covariances, measuring the direction of co-movement between these portfolios' returns and our global risk factors. As shown in Table (2.19), the return of high (low) interest rate portfolio is negatively (positively) correlated to the level factor. At the same time, the return of high (low) interest rate portfolio is positively (negatively) correlated to the slope factor with statistical significance. These results are consistent with our time series tests in section 2.5.2. As suggested in section 2.5.3, a high level and low slope correspond to high risk; thus, these results imply that a high interest rate currency is a risky asset, with little or even negative covariance to the risk embodied in the level and slope risk factors, performing poorly when high risk (that is, high level and low slope) and thus requiring a high return. On the contrary, low interest rate currency hedges against the risk, performing well when there is a high risk of high level and low slope. This leads to a negative covariance between Carry Trade performance and the risk, explaining why Carry Trade failed during the 2008 crisis. These findings are consistent with both empirical work by Menkhoff et al. (2012) and theoretical work by Farhi and Gabaix (2015), that risky countries have high interest rates to compensate for the risk of currency depreciation in a potential world disaster. This further justifies time-varying risk premia in Carry Trade excess return, and the underlying risk can be approximated by our global risk factors of level and slope.

**Table 2.19**

## 2.6 CONCLUSIONS AND DISCUSSIONS

The paper provides three main contributions: (1) studying the empirical performance of currency risk term structure, (2) extracting its information to build profitable trading strategies, and (3) constructing global risk factors to explain currency excess returns. To achieve these goals, the paper first constructs a new currency risk index FCX to comprehensively measure FX risk, using the corridor method of Andersen et al. (2015) and establishes its ability to capture market stress in terms of volatility and to reflect the asymmetric importance of return distribution tails. Using FCX, I look into currency risks across different horizons, derive the currency risk term structure for each currency pair, and build a measurement of level and slope to quantify their shapes. I consistently find that for currencies paired by US dollars, the term structure of currency risk is flat at a low level prior to the 2008 crisis, upward-sloping after the crisis, and peaks at a high level with a prominently negative slope during the crisis. This work is believed to be new in the currency research field, and the result is consistent with both recent empirical findings in equity and fixed-income markets and their modified disasters theories, shedding light on FX theory modeling in the future.

I explore the usage of the information on currency risk term structure in two ways. One is to build trading strategies, earning a profit by longing currencies with the highest level or slope and shorting ones with the lowest level or slope. The profit by sorting slope has a low correlation to Carry Trade and is robust to the 2008 crisis period. The other way is to extract global risk factors to help understand currency excess returns, which has been a long-time puzzle. The global risk factor by level substantially improves the cross-sectional explanatory power in currency excess returns, compared to Lustig et al. (2011). In addition, I use a beta sorting approach, sorting currency pairs by their return exposures to global risk factors' level and slope and find a highly significant spread by longing the highest level beta and shorting the lowest level beta, or by longing the lowest slope beta and shorting the highest slope beta. The significant cross-sectional spread in returns not only further justify that our proposed risk factors are priced but also suggest that there is certain high risk corresponding to a high level and low slope. Furthermore, I find that a high interest rate currency earns returns co-varying negatively to the risk embodied in the level and slope, implying that it is a risky asset and thus requires a high risk premium, which well explains the Carry Trade excess returns. The risk behind our global risk factors of level and slope may be disaster risk, as suggested by our findings that the 2008 financial crisis has a high level and negative slope. It may be the risk of the disaster duration, proposed by Xie (2014), that the downward-sloping VIX corresponds to long disaster, or it may be risk proximity, how soon the risk is going to happen (Byunghoon, 2017). What risks are behind the level and slope factors leave open areas for future research.

**Figure 2.1: Strike Range $[k_L, k_H]$ Centers Around Forward Rate**

The figure shows how the truncated strike range moves when there are different forward rates across time. Three panels a, b, c, show examples of GBPUSD with tenor of one month on representative days post-crisis, during crisis, and pre-crisis. Within each panel, the left graph shows the truncating rule function $R(k)$ with vertical axis as the R value, and the right one shows the volatility smile with the vertical axis as implied volatility (IV) derived by the Black-Scholes model, and the horizontal axis for both is moneyness $k = \frac{K}{F}$, the strike normalized by the forward rate. On each graph, the three vertical dash lines from left to right indicate $k_L = k_{0.03}(lower\ bound), k_F = 1(forward\ rate),\ k_H = k_{0.97}(upper\ bound)$, respectively.

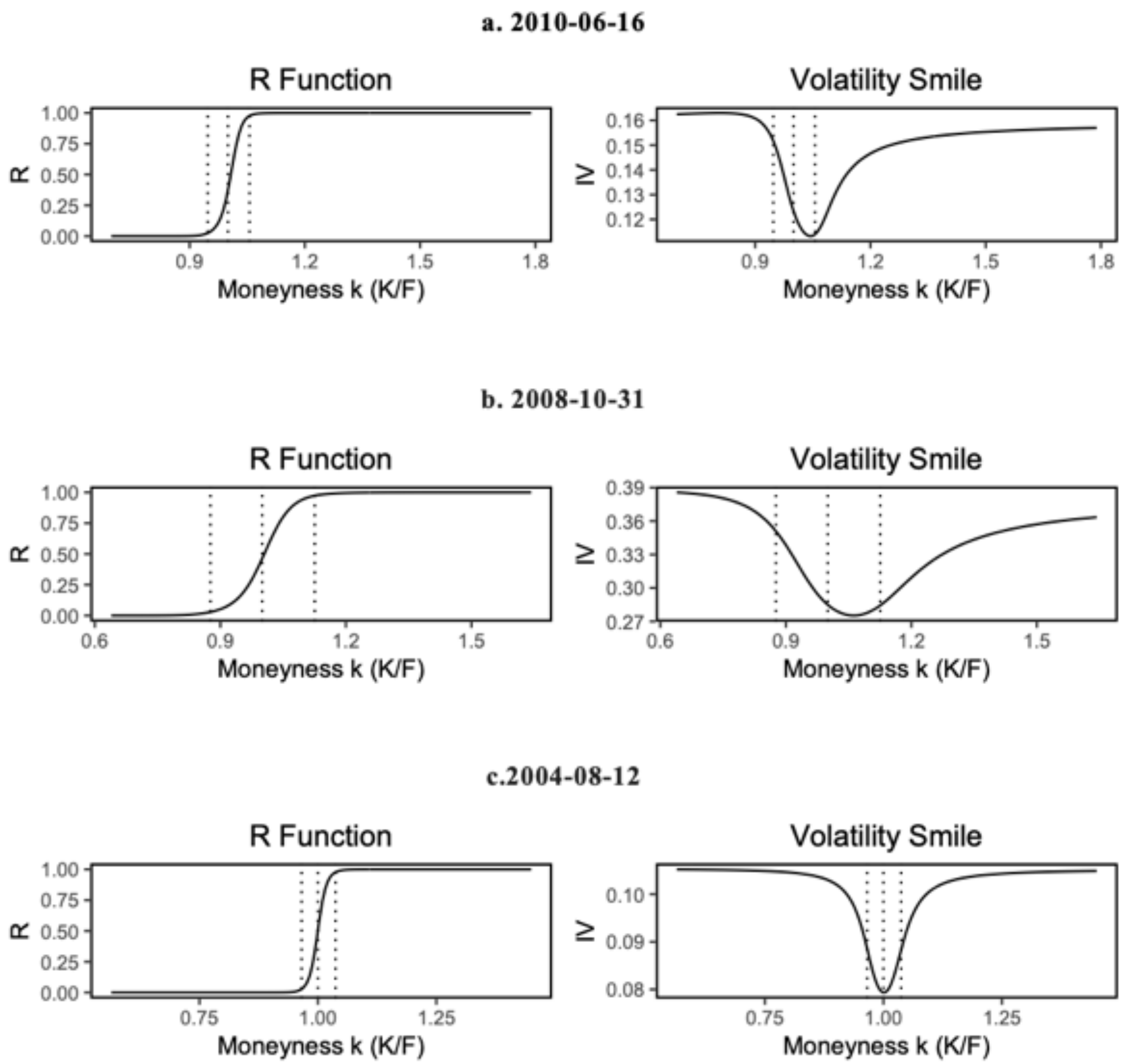
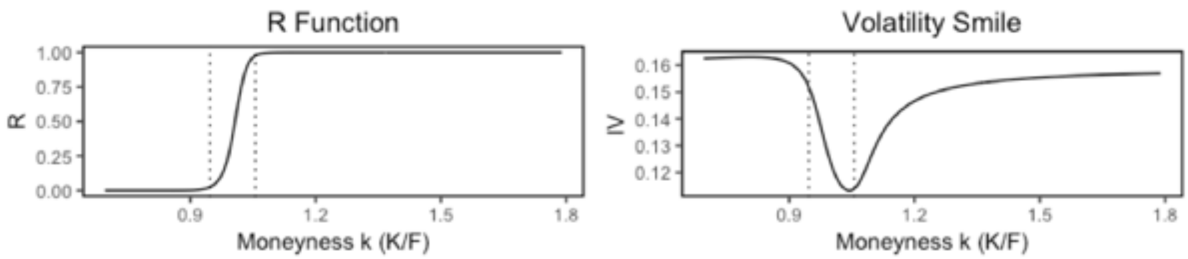


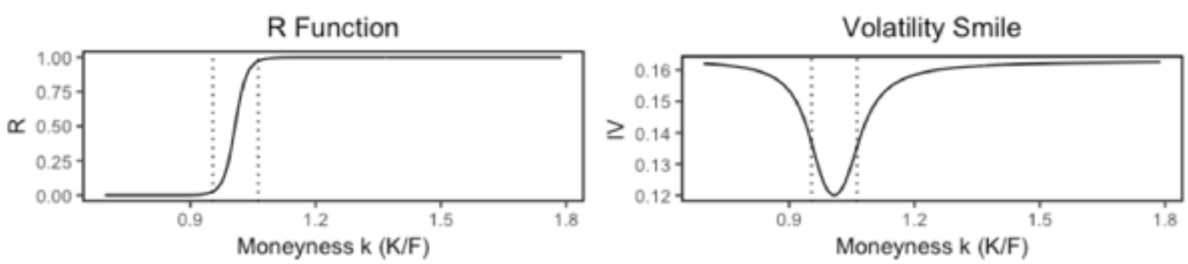
**Figure 2.2: Strike Range $[k_L, k_H]$ Shifts to Right as Skewness Increases**

The figure shows how the truncated strike range evolves when there is a different skewness across time. Three panels a, b, c, show examples of GBPUSD with tenor of one month on 2010-06-16, with negative skewness, no skewness, and positive skewness, respectively, with the latter two cases simulated by setting risk reversal to zero and positive, respectively, keeping everything else the same. Within each panel, the left graph shows the truncating rule function $R(k)$ with the vertical axis as the R value, and the right one shows the volatility smile with the vertical axis as implied volatility (IV) derived by the Black-Scholes model, and the horizontal axis for both is moneyness $k = \frac{K}{F}$, the strike normalized by forward rate. On each graph, the two vertical dash lines from left to right indicate $k_L = k_{0.03}(lower\ bound), k_H = k_{0.97}(upper\ bound)$, respectively.

a. rr=-0.019, negative skew: $k_L = 0.947, k_H = 1.056, FCX = 0.1217$




b. assume rr=0, no skew: $k_L = 0.954, k_H = 1.063, FCX = 0.1212$




c. assume rr=0.019, positive skew: $k_L = 0.961, k_H = 1.069, FCX = 0.1206$

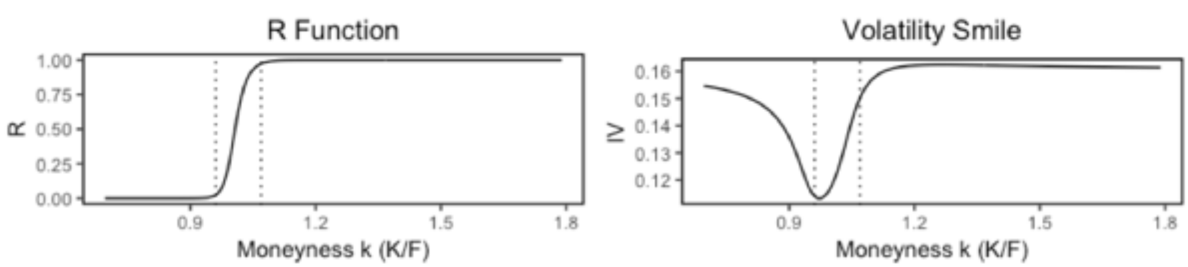


**Figure 2.3: FCX Compensates for Risk of Negative Skewness**

The figure depicts the relationship between FCX and skewness, using examples of all currencies with tenor of one month on 2010-06-16. Within each plot, FCX is the vertical axis, and rr, the risk reversal, is the horizontal axis to proxy for skewness.

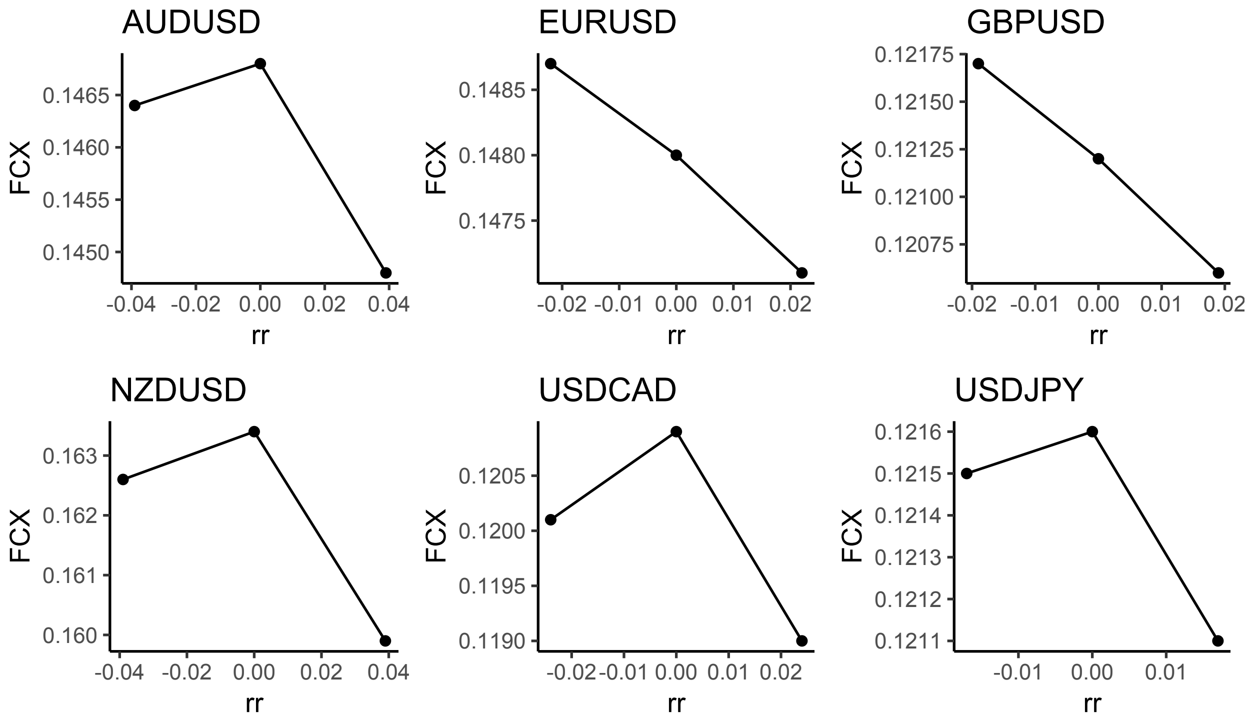
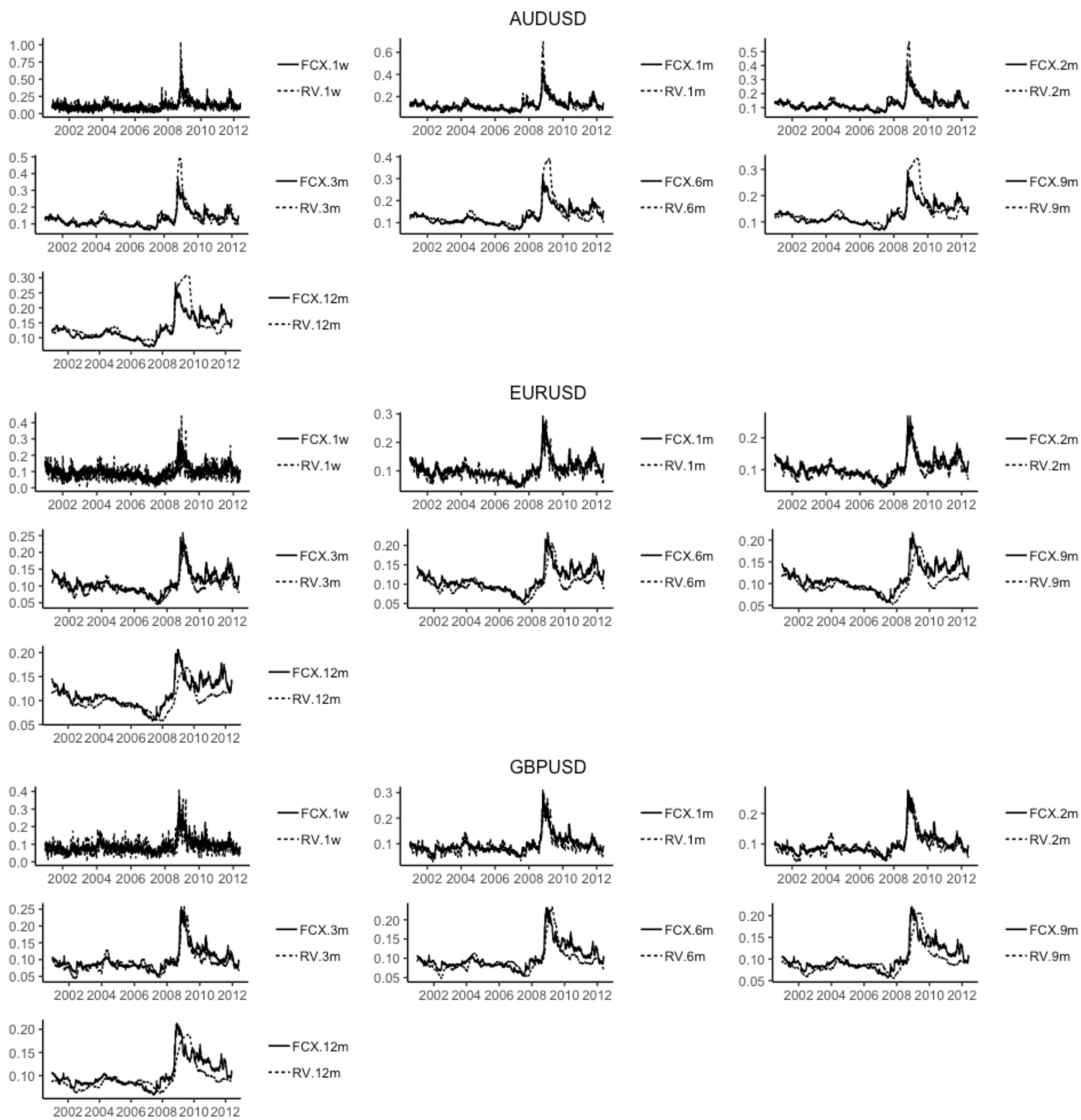
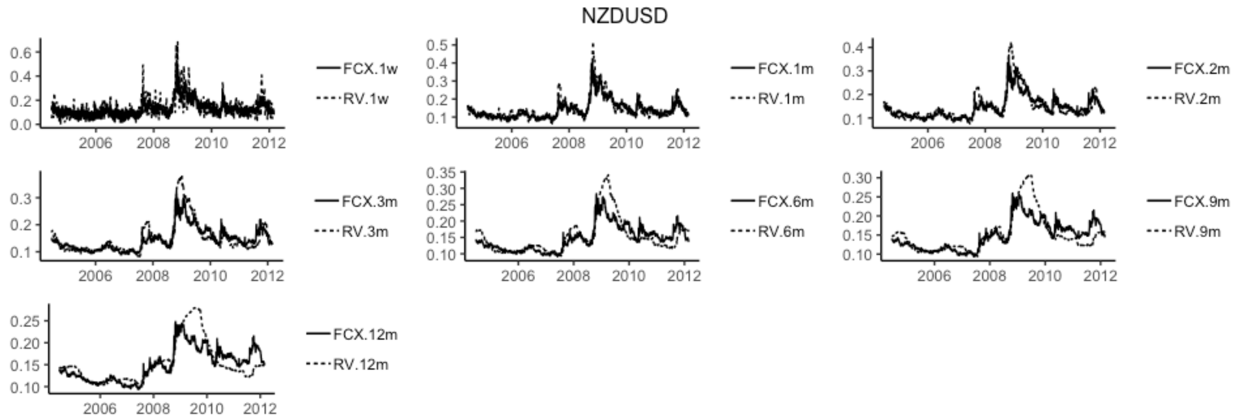
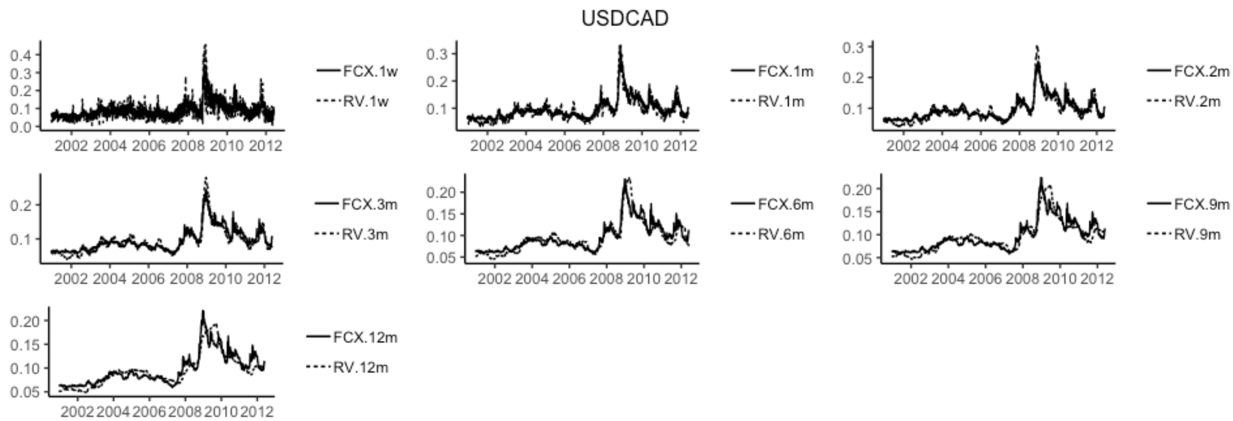


**Figure 2.4: Time Series Dynamics of FCX and Realized Volatility (RV)**

The figure plots the time series dynamics of FCX (solid curve) and realized volatility (dashed curve) for different maturities and currencies.




NZDUSD
FCX.1w
RV.1w
FCX.1m
RV.1m
FCX.2m
RV.2m
FCX.3m
RV.3m
FCX.6m
RV.6m
FCX.9m
RV.9m
FCX.12m
RV.12m
2006 2008 2010 2012


USDCAD
FCX.1w
RV.1w
FCX.1m
RV.1m
FCX.2m
RV.2m
FCX.3m
RV.3m
FCX.6m
RV.6m
FCX.9m
RV.9m
FCX.12m
RV.12m
2002 2004 2006 2008 2010 2012

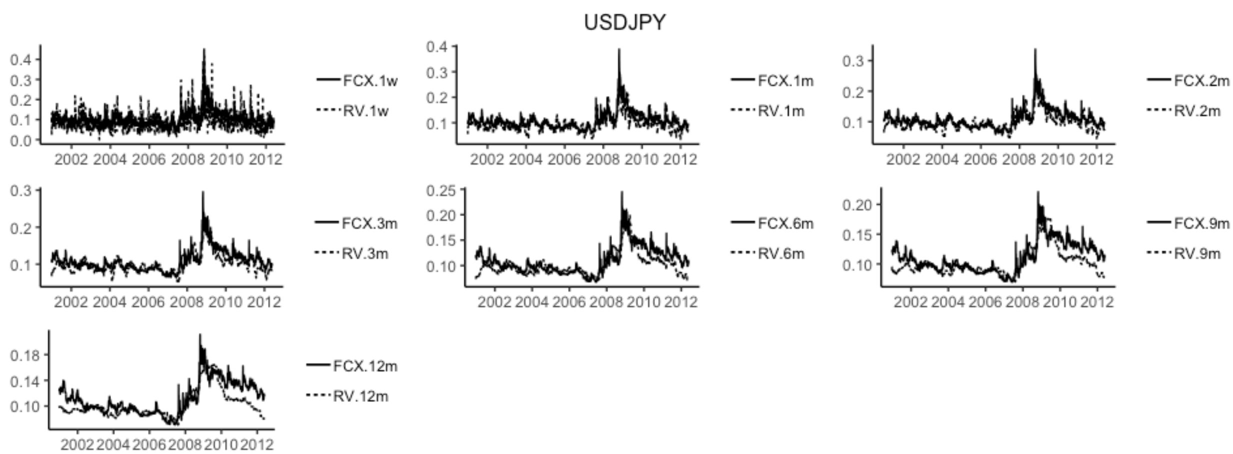

USDJPY
FCX.1w
RV.1w
FCX.1m
RV.1m
FCX.2m
RV.2m
FCX.3m
RV.3m
FCX.6m
RV.6m
FCX.9m
RV.9m
FCX.12m
RV.12m
2002 2004 2006 2008 2010 2012

**Figure 2.5: Time Series Dynamics of FCX of Different Maturities by Currency Pair**

For each currency pair, the figure plots the time series dynamics of FCX for different maturities, as denoted by different colors.

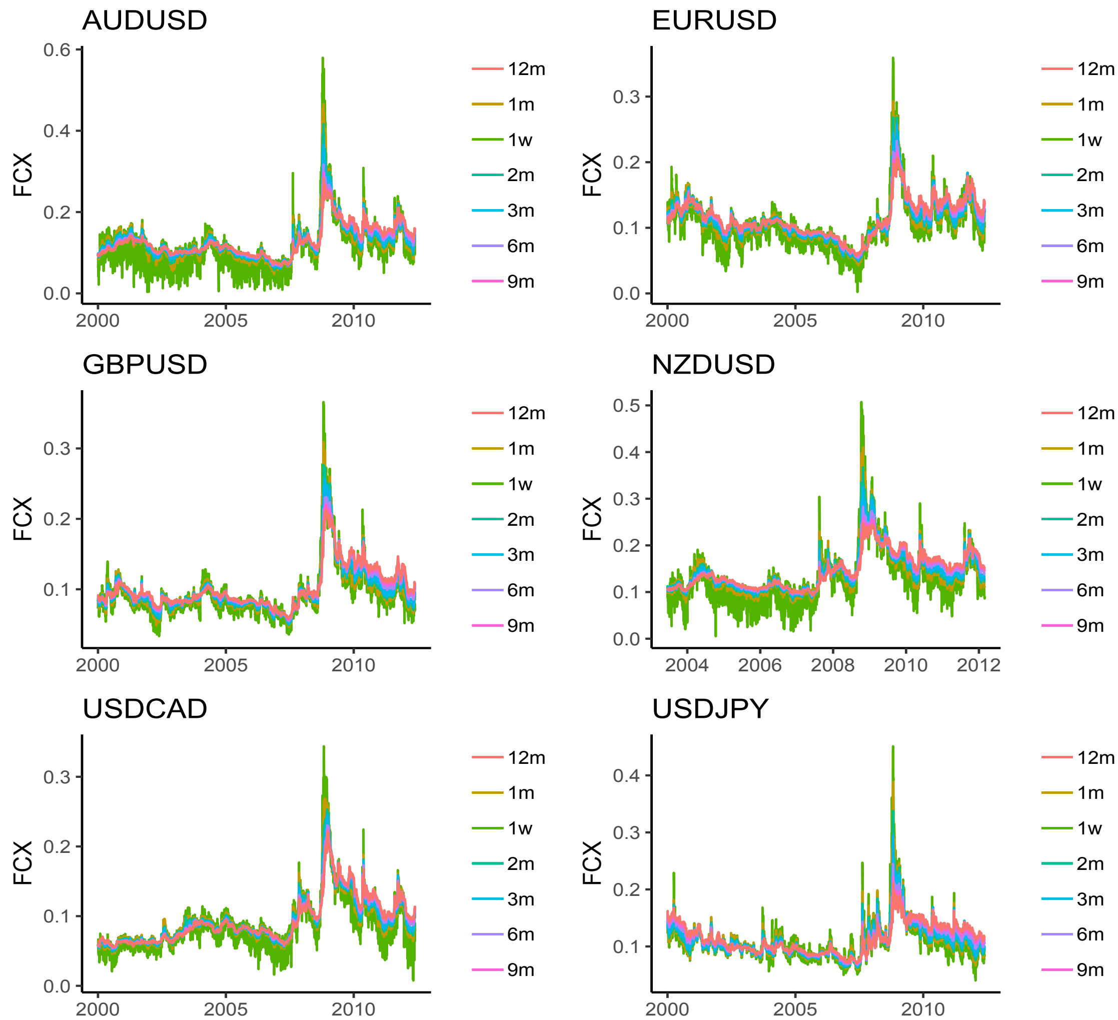


**Figure 2.6: Shape of FCX Term Structure on Representative Days by Currency Pair**

For each currency pair, the figure depicts the term structure shape of FX risk across different maturities on representative days of post-crisis (square point), during crisis (triangular point), and before-crisis (round point), with FCX as the vertical axis and maturity as the horizontal axis.

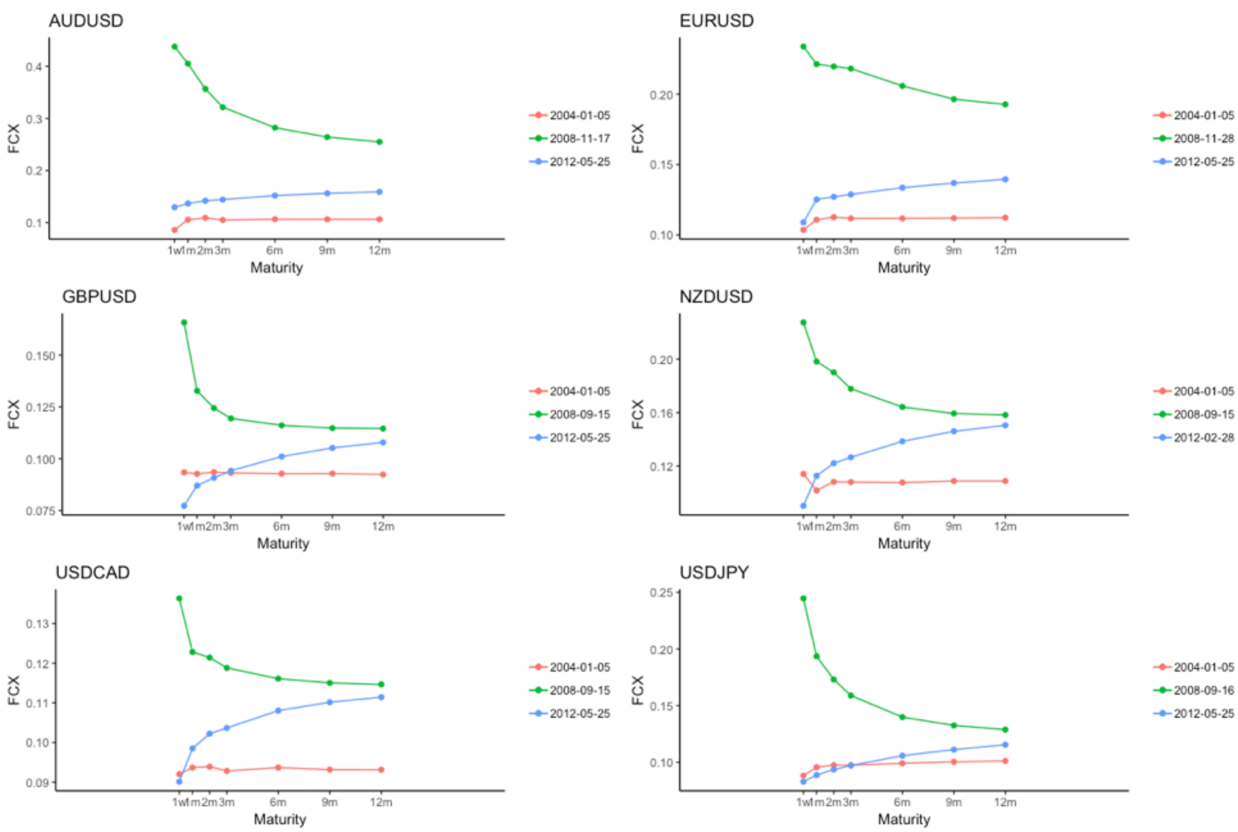
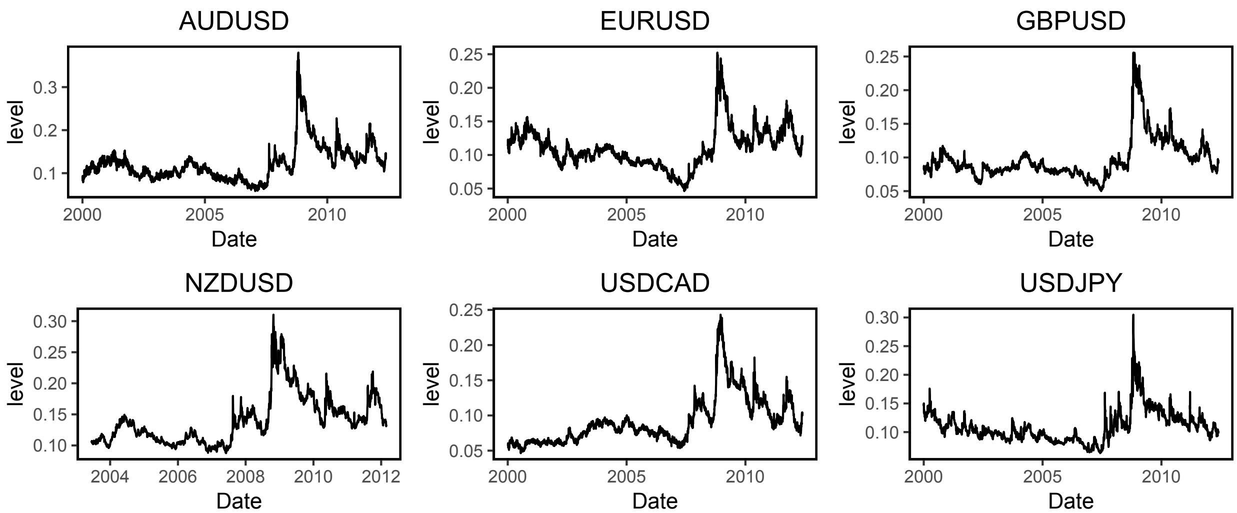


**Figure 2.7: Time Series Dynamics of Level and Slope of Currency Risk Term Structure By Currency Pair**

For each currency pair, the figure depicts the time series dynamics of the level factor and slope factor of currency risk term structure.

**a. Level by currency pair**

$$Level_{i,t} = \frac{1}{7}\sum_{T} FCX_{i,t,T}, T = 1w, 1m, \ldots, 12m$$




**b. Slope by currency pair**

$$Slope_{i,t} = FCX_{i,t,12m} - FCX_{i,t,1w}$$

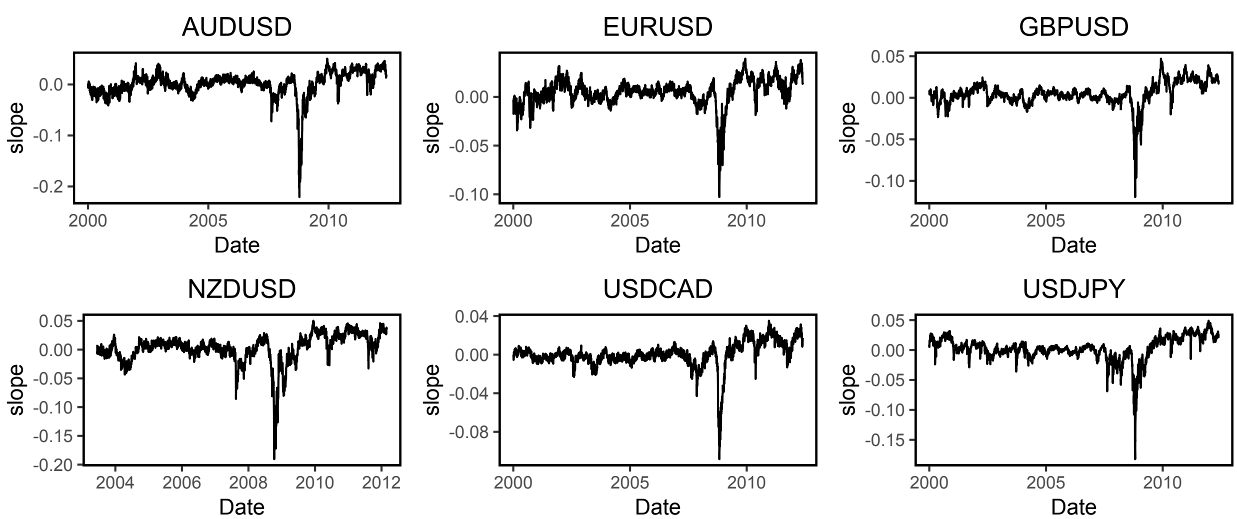


**Figure 2.8: Time Series Dynamics of Global Factors**

The figure plots the time series dynamics of the global level and slope factors, approximated as the average of all currencies' FX risk term structure levels and slopes, respectively.

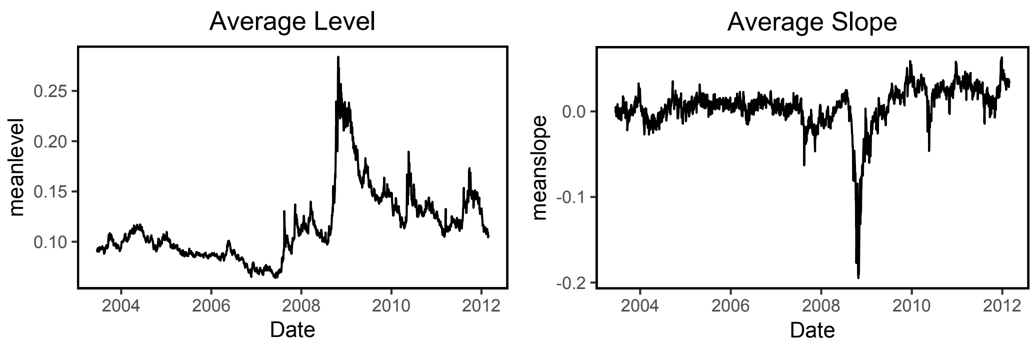


**Table 2.1: Cumulative Proportion of Variance of Principal Components (PC1, PC2) by Currency Pair**

| | AUDUSD | EURUSD | GBPUSD | NZDUSD | USDCAD | USDJPY |
|---|---|---|---|---|---|---|
| **PC1** | 0.9461 | 0.9603 | 0.9584 | 0.9558 | 0.9545 | 0.9169 |
| **PC2** | 0.9946 | 0.9954 | 0.9971 | 0.9982 | 0.9962 | 0.9961 |

**Table 2.2: Loadings of Principal Components (PC1, PC2) on FCXs of Different Maturities by Currency Pair**

| Currency | Component | FCX_1W | FCX_1M | FCX_2M | FCX_3M | FCX_6M | FCX_9M | FCX_12M |
|---|---|---|---|---|---|---|---|---|
| **AUDUSD** | **PC1** | 0.3599 | 0.3773 | 0.3856 | 0.3879 | 0.3837 | 0.3776 | 0.3730 |
| | **PC2** | -0.6092 | -0.3813 | -0.1687 | -0.0053 | 0.2683 | 0.4002 | 0.4721 |
| **GBPUSD** | **PC1** | 0.3612 | 0.3789 | 0.3839 | 0.3850 | 0.3824 | 0.3786 | 0.3752 |
| | **PC2** | -0.6742 | -0.3361 | -0.1270 | 0.0177 | 0.2603 | 0.3788 | 0.4527 |
| **EURUSD** | **PC1** | 0.3632 | 0.3785 | 0.3843 | 0.3856 | 0.3825 | 0.3777 | 0.3735 |
| | **PC2** | -0.6296 | -0.3600 | -0.1550 | -0.0036 | 0.2574 | 0.3945 | 0.4775 |
| **NZDUSD** | **PC1** | 0.3536 | 0.3776 | 0.3872 | 0.3897 | 0.3855 | 0.3786 | 0.3723 |
| | **PC2** | -0.6316 | -0.3659 | -0.3560 | -0.1537 | 0.2076 | 0.3969 | 0.5139 |
| **USDCAD** | **PC1** | 0.3572 | 0.3788 | 0.3853 | 0.3864 | 0.3826 | 0.3787 | 0.3760 |
| | **PC2** | -0.6887 | -0.3423 | -0.1139 | 0.0369 | 0.2719 | 0.3731 | 0.4255 |
| **USDJPY** | **PC1** | 0.3539 | 0.3795 | 0.3897 | 0.3937 | 0.3880 | 0.3755 | 0.3637 |
| | **PC2** | -0.5776 | -0.3596 | -0.1987 | -0.0466 | 0.2423 | 0.4126 | 0.5162 |

**Table 2.3: Variance-Covariance Matrix of FCXs of Different Maturities by Currency Pair (scaled to correlation)**

| | CX_1wk | CX_1m | CX_2m | CX_3m | CX_6m | CX_9m | CX_12m |
|---|---|---|---|---|---|---|---|
| **AUDUSD** | | | | | | | |
| **CX_1wk** | 1.0000 | 0.9469 | 0.9216 | 0.8963 | 0.8381 | 0.8000 | 0.7756 |
| **CX_1m** | | 1.0000 | 0.9882 | 0.9702 | 0.9184 | 0.8814 | 0.8564 |
| **CX_2m** | | | 1.0000 | 0.9938 | 0.9619 | 0.9343 | 0.9142 |
| **CX_3m** | | | | 1.0000 | 0.9839 | 0.9641 | 0.9484 |
| **CX_6m** | | | | | 1.0000 | 0.9954 | 0.9888 |
| **CX_9m** | | | | | | 1.0000 | 0.9983 |
| **CX_12m** | | | | | | | 1.0000 |
| **EURUSD** | | | | | | | |
| **CX_1wk** | 1.0000 | 0.9606 | 0.9371 | 0.9169 | 0.8747 | 0.8493 | 0.8309 |
| **CX_1m** | | 1.0000 | 0.9916 | 0.9802 | 0.9482 | 0.9263 | 0.9102 |
| **CX_2m** | | | 1.0000 | 0.9962 | 0.9771 | 0.9609 | 0.9482 |
| **CX_3m** | | | | 1.0000 | 0.9903 | 0.9786 | 0.9687 |
| **CX_6m** | | | | | 1.0000 | 0.9974 | 0.9932 |
| **CX_9m** | | | | | | 1.0000 | 0.9988 |
| **CX_12m** | | | | | | | 1.0000 |
| **GBPUSD** | | | | | | | |
| **CX_1wk** | 1.0000 | 0.9776 | 0.9583 | 0.9378 | 0.8922 | 0.8623 | 0.8418 |
| **CX_1m** | | 1.0000 | 0.9930 | 0.9815 | 0.9492 | 0.9250 | 0.9075 |
| **CX_2m** | | | 1.0000 | 0.9964 | 0.9769 | 0.9589 | 0.9448 |
| **CX_3m** | | | | 1.0000 | 0.9905 | 0.9777 | 0.9667 |
| **CX_6m** | | | | | 1.0000 | 0.9971 | 0.9921 |
| **CX_9m** | | | | | | 1.0000 | 0.9987 |
| **CX_12m** | | | | | | | 1.0000 |
| **NZDUSD** | | | | | | | |
| **CX_1wk** | 1.0000 | 0.9479 | 0.9222 | 0.8930 | 0.8279 | 0.7853 | 0.7551 |
| **CX_1m** | | 1.0000 | 0.9868 | 0.9676 | 0.9146 | 0.8756 | 0.8468 |
| **CX_2m** | | | 1.0000 | 0.9933 | 0.9606 | 0.9314 | 0.9082 |
| **CX_3m** | | | | 1.0000 | 0.9834 | 0.9625 | 0.9441 |
| **CX_6m** | | | | | 1.0000 | 0.9949 | 0.9867 |
| **CX_9m** | | | | | | 1.0000 | 0.9977 |
| **CX_12m** | | | | | | | 1.0000 |

| USDCAD | | | | | | | |
|---|---|---|---|---|---|---|---|
| **CX_1wk** | 1.0000 | 0.9675 | 0.9430 | 0.9214 | 0.8805 | 0.8596 | 0.8476 |
| **CX_1m** | | 1.0000 | 0.9918 | 0.9807 | 0.9533 | 0.9375 | 0.9282 |
| **CX_2m** | | | 1.0000 | 0.9966 | 0.9814 | 0.9707 | 0.9637 |
| **CX_3m** | | | | 1.0000 | 0.9929 | 0.9856 | 0.9806 |
| **CX_6m** | | | | | 1.0000 | 0.9985 | 0.9965 |
| **CX_9m** | | | | | | 1.0000 | 0.9995 |
| **CX_12m** | | | | | | | 1.0000 |

| USDJPY | | | | | | | |
|---|---|---|---|---|---|---|---|
| **CX_1wk** | 1.0000 | 0.9713 | 0.9396 | 0.9023 | 0.7994 | 0.7238 | 0.6678 |
| **CX_1m** | | 1.0000 | 0.9886 | 0.9668 | 0.8900 | 0.8263 | 0.7762 |
| **CX_2m** | | | 1.0000 | 0.9929 | 0.9436 | 0.8937 | 0.8515 |
| **CX_3m** | | | | 1.0000 | 0.9745 | 0.9372 | 0.9029 |
| **CX_6m** | | | | | 1.0000 | 0.9911 | 0.9752 |
| **CX_9m** | | | | | | 1.0000 | 0.9958 |
| **CX_12m** | | | | | | | 1.0000 |

**Table 2.4: Correlation (corr) between Calculated Factors (Level, Slope) and Principal Components (PC1, PC2) by Currency Pair**

| | AUDUSD | EURUSD | GBPUSD | NZDUSD | USDCAD | USDJPY |
|---|---|---|---|---|---|---|
| **corr(Level, PC1)** | 0.9991 | 0.9998 | 0.9998 | 0.9997 | 0.9997 | 0.9991 |
| **corr(Slope, PC2)** | 0.8234 | 0.9271 | 0.9385 | 0.9255 | 0.9427 | 0.9309 |

**Table 2.5: Currency Quotes and Excess Return Definition**

| | **AUDUSD** | **EURUSD** | **GBPUSD** | **NZDUSD** | **USDCAD** | **USDJPY** |
|---|---|---|---|---|---|---|
| **Definition** | USD per AUD | USD per EUR | USD per GBP | USD per NZD | CAD per USD | JPY per USD |
| **Domestic currency** | USD | USD | USD | USD | CAD | JPY |
| **An increase in $s$ means** | AUD depreciates | EUR depreciates | GBP depreciates | NZD depreciates | CAD appreciates | JPY appreciates |
| **Interest rate differential** | $i_{AUD} - i_{USD}$ | $i_{EUR} - i_{USD}$ | $i_{GBP} - i_{USD}$ | $i_{NZD} - i_{USD}$ | $i_{CAD} - i_{USD}$ | $i_{JPY} - i_{USD}$ |
| **Excess return** | $\mathrm{s}_{t+1} - \mathrm{f}_t^{t+1}$ | $\mathrm{s}_{t+1} - \mathrm{f}_t^{t+1}$ | $\mathrm{s}_{t+1} - \mathrm{f}_t^{t+1}$ | $\mathrm{s}_{t+1} - \mathrm{f}_t^{t+1}$ | $\mathrm{f}_t^{t+1} - \mathrm{s}_{t+1}$ | $\mathrm{f}_t^{t+1} - \mathrm{s}_{t+1}$ |

**Table 2.6: Level Trade and Slope Trade**

The table summarizes statistics of excess returns for each portfolio of Level Trade (Panel a) and Slope Trade (Panel b), including mean, standard deviation (St. dev.), skewness, kurtosis, the Sharpe ratio (SR), the auto-correlation coefficient of degree one (AC(1)), and sample size (Obs). All values are annualized. "., *, **, ***" indicate statistical significance at 10%, 5%, 1%, and 0.1% levels, respectively, by Newey and West (1987) and Andrews (1991). Panel A sorts currencies by level from low to high and constructs Level Trade by longing currencies of the highest level and shorting ones of the lowest level. Panel b sorts currencies by slope from low to high, and constructs Slope Trade by longing currencies of the highest slope and shorting ones of the lowest slope.

**a. Level Trade**

| 6 portfolios | I1 (short) | I2 | I3 | I4 | I5 | I6 (long) | Level |
|---|---|---|---|---|---|---|---|
| **Mean** | 0.0262 | 0.0092 | -0.0048 | 0.0478 | 0.0263 | 0.0561 | 0.0299 |
| **St. dev.** | 0.1023 | 0.0936 | 0.1227 | 0.1168 | 0.1391 | 0.1545 | 0.1132 |
| **Skew** | -1.1501 | 0.0878 | -0.2781 | -0.0909 | -0.6379 | -0.4202 | -0.5601 |
| **Kurt** | 7.1993 | 6.3125 | 3.6497 | 3.5568 | 5.7544 | 5.7217 | 5.3748 |
| **SR** | 0.2560 | 0.0755 | -0.0506 | 0.3603 | 0.2574 | 0.3634 | 0.2643 |
| **AC(1)** | -0.043 | 0.007 | 0.307 | -0.012 | 0.121 | 0.01 | -0.086 |
| **Obs** | 105 | 105 | 105 | 105 | 105 | 105 | 105 |

| 3 portfolios | P1 (short) | P2 | P3 (long) | Level |
|---|---|---|---|---|
| **Mean** | 0.0177 | 0.0215 | 0.0412 | 0.0235 |
| **St. dev.** | 0.0874 | 0.0946 | 0.1382 | 0.1035 |
| **Skew** | -0.8322 | 0.0544 | -0.6172 | -0.4069 |
| **Kurt** | 7.5221 | 4.7300 | 6.2945 | 6.0234 |
| **SR** | 0.2024 | 0.2269 | 0.2981 | 0.2271 |
| **AC(1)** | -0.01 | 0.032 | 0.07 | 0.106 |
| **Obs** | 105 | 105 | 105 | 105 |

**b. slope**

| 6 portfolios | I1 (short) | I2 | I3 | I4 | I5 | I6 (long) | Slope |
|---|---|---|---|---|---|---|---|
| **Mean** | -0.0233 | 0.0376 | 0.0271 | 0.0695 | -0.0195 | 0.0693 | 0.0926* |
| **St. dev.** | 0.1310 | 0.1097 | 0.1238 | 0.1078 | 0.1309 | 0.1318 | 0.1184 |
| **Skew** | -0.6178 | 0.1553 | -0.5644 | 0.3100 | -0.9130 | -0.2731 | -0.3038 |
| **Kurt** | 6.5199 | 7.3114 | 4.6709 | 3.9674 | 5.5559 | 5.5263 | 3.6890 |
| **SR** | -0.1778 | 0.3425 | 0.2188 | 0.6449 | -0.1487 | 0.5258 | 0.7817 |
| **AC(1)** | 0.058 | 0.041 | 0.085 | -0.129 | 0.228 | 0.065 | 0.127 |
| **Obs** | 105 | 105 | 105 | 105 | 105 | 105 | 105 |

| 3 portfolios | P1 (short) | P2 | P3 (long) | Slope |
|---|---|---|---|---|
| **Mean** | 0.0071 | 0.0483 | 0.0249 | 0.0178 |
| **St. dev.** | 0.1031 | 0.0950 | 0.1178 | 0.0782 |
| **Skew** | -0.8817 | 0.2078 | -0.5187 | -0.3023 |
| **Kurt** | 8.7719 | 3.5472 | 5.5410 | 2.9073 |
| **SR** | 0.0692 | 0.5085 | 0.2114 | 0.2272 |
| **AC(1)** | 0.025 | -0.145 | 0.129 | 0.074 |

| | | | | |
|---|---|---|---|---|
| **Obs** | 105 | 105 | 105 | 105 |

**Table 2.7: Carry Trade**

The table summarizes statistics of excess returns for each portfolio of Carry Trade, including the mean, standard deviation (St. dev.), skewness, kurtosis, Sharpe ratio (SR), auto-correlation coefficient of degree one (AC(1)), and sample size (Obs). All values are annualized. "., *, **, ***" indicate statistical significance at 10%, 5%, 1%, and 0.1% levels, respectively, by Newey and West (1987) and Andrews (1991). The table shows currencies sorted by interest rate differentials from low to high and constructs the Carry Trade by longing currencies of the highest interest rate and shorting ones of the lowest interest rate.

| 6 portfolios | I1 (short) | I2 | I3 | I4 | I5 | I6 (long) | Carry |
|---|---|---|---|---|---|---|---|
| **Mean** | 0.0255 | 0.0210 | 0.0045 | -0.0102 | 0.0589 | 0.0609 | 0.0354 |
| **St. dev.** | 0.1000 | 0.1032 | 0.1123 | 0.1107 | 0.1485 | 0.1530 | 0.1787 |
| **Skew** | -0.2480 | -0.6103 | -0.0708 | -0.2604 | -0.7185 | -0.4661 | -0.9448 |
| **Kurt** | 3.2218 | 7.3580 | 3.8791 | 5.0487 | 5.8804 | 5.2084 | 6.0474 |
| **SR** | 0.2550 | 0.2036 | 0.0402 | -0.0923 | 0.3972 | 0.3981 | 0.1984 |
| **AC(1)** | 0.069 | -0.100 | 0.119 | -0.149 | 0.097 | -0.033 | 0.076 |
| **Obs** | 105 | 105 | 105 | 105 | 105 | 105 | 105 |

| 3 portfolios | P1 (short) | P2 | P6 (long) | Carry |
|---|---|---|---|---|
| **Mean** | 0.0233 | -0.0029 | 0.0600 | 0.0367 |
| **St. dev.** | 0.0756 | 0.0963 | 0.1454 | 0.1257 |
| **Skew** | -0.1022 | -0.4504 | -0.6183 | -0.9261 |
| **Kurt** | 3.0413 | 4.6697 | 5.5719 | 5.1737 |
| **SR** | 0.3076 | -0.2962 | 0.4124 | 0.2920 |
| **AC(1)** | -0.039 | 0.064 | 0.031 | 0.031 |
| **Obs** | 105 | 105 | 105 | 105 |

**Table 2.8: Trading Strategies Performance Comparison**

The table summarizes statistics of excess returns for portfolios of Level Trade, Slope Trade, and Carry Trade, including the mean, standard deviation (St. dev.), skewness, kurtosis, Sharpe ratio (SR), auto-correlation coefficient of degree one (AC(1)), and sample size (Obs). All values are annualized. "., *, **, ***" indicate statistical significance at 10%, 5%, 1%, and 0.1% levels, respectively, by Newey and West (1987) and Andrews (1991).

| | 6 portfolios | | | 3 portfolios | | |
|---|---|---|---|---|---|---|
| | **Level** | **Slope** | **Carry** | **Level** | **Slope** | **Carry** |
| **Mean** | 0.0299 | 0.0926* | 0.0354 | 0.0235 | 0.0178 | 0.0367 |
| **St. dev.** | 0.1132 | 0.1184 | 0.1787 | 0.1035 | 0.0782 | 0.1257 |
| **Skew** | -0.5601 | -0.3038 | -0.9448 | -0.4069 | -0.3023 | -0.9261 |
| **Kurt** | 5.3748 | 3.6890 | 6.0474 | 6.0234 | 2.9073 | 5.1737 |
| **SR** | 0.2643 | 0.7817 | 0.1984 | 0.2271 | 0.2272 | 0.2920 |
| **AC(1)** | -0.086 | 0.127 | 0.076 | 0.106 | 0.074 | 0.031 |
| **Obs** | 105 | 105 | 105 | 105 | 105 | 105 |
| **corr($\mathbf{r_p}$, $\mathbf{r_{Carry}}$)** | 0.6577 | 0.0661 | 1 | 0.7508 | 0.1665 | 1 |

**Table 2.9: Different Sampling and Investment Horizon**

The table summarizes statistics of excess returns for portfolios of Level Trade, Slope Trade, and Carry Trade, including the mean, standard deviation (St. dev.), skewness, kurtosis, Sharpe ratio (SR), auto-correlation coefficient of degree one (AC(1)), and sample size (Obs). All values are annualized. "., *, **, ***" indicate statistical significance at 10%, 5%, 1%, and 0.1% levels, respectively, by Newey and West (1987) and Andrews (1991). Panels a and b are the results of monthly investment, rebalancing each month, sampling by the first day and middle day of each month, respectively. Panel c is the result of weekly investment, rebalancing each week, sampling by the last day of each week.

**a. Monthly return, sampling by 1st day of each month**

| | 6 portfolios | | | 3 portfolios | | |
|---|---|---|---|---|---|---|
| | **Level** | **Slope** | **Carry** | **Level** | **Slope** | **Carry** |
| **Mean** | 0.0599 | 0.0871* | 0.0552 | 0.0437 | 0.0469 | 0.0545 |
| **St. dev.** | 0.1338 | 0.1317 | 0.1844 | 0.1072 | 0.0926 | 0.1329 |
| **Skew** | 0.4759 | -0.0306 | -1.0282 | -0.3437 | 0.1635 | -0.6206 |
| **Kurt** | 8.7452 | 3.4516 | 6.0494 | 8.1805 | 4.8801 | 5.9466 |
| **SR** | 0.4473 | 0.6611 | 0.2996 | 0.4078 | 0.5064 | 0.4099 |
| **AC(1)** | -0.231 | 0.076 | -0.017 | -0.086 | -0.003 | -0.058 |
| **Obs** | 104 | 104 | 104 | 104 | 104 | 104 |
| **corr**($r_p$, $r_{Carry}$) | 0.6125 | -0.0093 | 1 | 0.8049 | 0.0866 | 1 |

**b. Monthly return, sampling by middle day of each month**

| | 6 portfolios | | | 3 portfolios | | |
|---|---|---|---|---|---|---|
| | **Level** | **Slope** | **Carry** | **Level** | **Slope** | **Carry** |
| **Mean** | 0.0235 | 0.0971* | 0.0534 | 0.0427 | 0.0528* | 0.0451 |
| **St. dev.** | 0.0978 | 0.1163 | 0.1634 | 0.0848 | 0.0765 | 0.1121 |
| **Skew** | 0.2036 | 0.3409 | -0.6470 | -0.1962 | 0.1953 | -0.5688 |
| **Kurt** | 3.4315 | 3.7254 | 4.5460 | 4.9150 | 2.9000 | 5.4532 |
| **SR** | 0.2408 | 0.8347 | 0.3269 | 0.5031 | 0.6902 | 0.4022 |
| **AC(1)** | 0.075 | -0.146 | 0.087 | -0.034 | -0.025 | 0.122 |
| **Obs** | 104 | 104 | 104 | 104 | 104 | 104 |
| **corr**($r_p$, $r_{Carry}$) | 0.6348 | 0.2815 | 1 | 0.7458 | 0.1465 | 1 |

**c. Weekly return, sampling by last day of each week, rebalance weekly**

| | 6 portfolios | | | 3 portfolios | | |
|---|---|---|---|---|---|---|
| | **Level** | **Slope** | **Carry** | **Level** | **Slope** | **Carry** |
| **Mean** | 0.0322 | 0.0759* | 0.0818 | 0.0370 | 0.0399 | 0.0679 |
| **St. dev.** | 0.1354 | 0.1231 | 0.2036 | 0.1048 | 0.0925 | 0.1379 |
| **Skew** | -0.6643 | 0.0113 | -1.5645 | -0.6267 | -0.0414 | -1.4333 |
| **Kurt** | 7.1092 | 5.0430 | 15.4282 | 7.5629 | 5.1537 | 13.4842 |
| **SR** | 0.2375 | 0.6160 | 0.4016 | 0.3533 | 0.4309 | 0.4926 |
| **AC(1)** | -0.075 | -0.033 | -0.153 | -0.055 | -0.071 | -0.112 |
| **Obs** | 459 | 459 | 459 | 459 | 459 | 459 |
| **corr**($\mathrm{r_p}$, $\mathrm{r_{Carry}}$) | 0.6777 | 0.0034 | 1 | 0.8055 | -0.0836 | 1 |

**Table 2.10: Trading Strategies Performance by Time Regime**

The table summarizes statistics of excess returns for portfolios of Level Trade (Panel a), Slope Trade (Panel b), and Carry Trade (Panel c) before the crisis (2003 Jun - 2007 Nov), during the crisis (2007 Dec - 2009 Jun), and after the crisis (2009 Jul - 2012 Feb), including the mean, standard deviation (St. dev.), skewness, kurtosis, Sharpe ratio (SR), auto-correlation coefficient of degree one (AC(1)), and sample size (Obs). All values are annualized. "., *, **, ***" indicate statistical significance at 10%, 5%, 1%, and 0.1% levels, respectively, by Newey and West (1987) and Andrews (1991). "6 ports" and "3 ports" mean 6 portfolios and 3 portfolios respectively.

**a. Level Trade**

| Level | Before crisis | | During crisis | | After crisis | |
|---|---|---|---|---|---|---|
| | 6 ports | 3 ports | 6 ports | 3 ports | 6 ports | 3 ports |
| **Mean** | 0.0158 | -0.0070 | -0.0188 | -0.0554 | 0.0826 | 0.1219* |
| **St. dev.** | 0.0934 | 0.0647 | 0.1707 | 0.1705 | 0.1036 | 0.1033 |
| **Skew** | -0.7996 | -1.1648 | -0.1985 | -0.0374 | -0.5876 | -0.4176 |
| **Kurt** | 4.1408 | 5.2140 | 4.2671 | 3.7594 | 3.2227 | 2.8740 |
| **SR** | 0.1693 | -0.1084 | -0.1102 | -0.3252 | 0.7975 | 1.1801 |
| **AC(1)** | -0.028 | 0.025 | -0.202 | 0.239 | -0.032 | -0.187 |
| **Obs** | 54 | 54 | 19 | 19 | 32 | 32 |

**b. Slope Trade**

| Slope | Before crisis | | During crisis | | After crisis | |
|---|---|---|---|---|---|---|
| | 6 ports | 3 ports | 6 ports | 3 ports | 6 ports | 3 ports |
| **Mean** | 0.0445 | 0.0275 | 0.2960** | 0.0134 | 0.0528 | 0.0039 |
| **St. dev.** | 0.1100 | 0.0633 | 0.1018 | 0.0918 | 0.1332 | 0.0936 |
| **Skew** | 0.0504 | 0.0585 | 0.0774 | -0.2440 | -0.6672 | -0.4161 |
| **Kurt** | 3.6057 | 2.3527 | 2.0369 | 2.1685 | 3.7960 | 2.7769 |
| **SR** | 0.4047 | 0.4353 | 2.9065 | 0.1455 | 0.3967 | 0.0416 |
| **AC(1)** | 0.007 | -0.128 | -0.122 | 0.285 | 0.16 | 0.103 |
| **Obs** | 54 | 54 | 19 | 19 | 32 | 32 |

**c. Carry Trade**

| Carry | Before crisis | | During crisis | | After crisis | |
|---|---|---|---|---|---|---|
| | 6 ports | 3 ports | 6 ports | 3 ports | 6 ports | 3 ports |
| **Mean** | 0.0903 | 0.0555 | -0.2034 | -0.0850 | 0.0846 | 0.0772 |
| **St. dev.** | 0.1288 | 0.0919 | 0.2886 | 0.2040 | 0.1638 | 0.1159 |
| **Skew** | -0.2697 | -0.5474 | -0.5792 | -0.4845 | -0.3357 | -0.8027 |
| **Kurt** | 3.4079 | 3.6242 | 3.3522 | 2.8567 | 3.7670 | 3.9313 |
| **SR** | 0.7015 | 0.6038 | -0.7048 | -0.4165 | 0.5167 | 0.6661 |
| **AC(1)** | -0.048 | -0.082 | 0.314 | 0.238 | -0.313 | -0.26 |
| **Obs** | 54 | 54 | 19 | 19 | 32 | 32 |

**Table 2.11: Variance-Covariance Matrix of Risk Factors across Different Currency Pairs (scaled to correlation)**

**a. Level**

| | AUDUSD | EURUSD | GBPUSD | NZDUSD | USDCAD | USDJPY |
|---|---|---|---|---|---|---|
| **AUDUSD** | 1.0000 | 0.9188 | 0.9352 | 0.9755 | 0.9298 | 0.9224 |
| **EURUSD** | | 1.0000 | 0.9202 | 0.8611 | 0.8624 | 0.8354 |
| **GBPUSD** | | | 1.0000 | 0.9155 | 0.9408 | 0.9172 |
| **NZDUSD** | | | | 1.0000 | 0.9276 | 0.9200 |
| **USDCAD** | | | | | 1.0000 | 0.9151 |
| **USDJPY** | | | | | | 1.0000 |

**b. Slope**

| | AUDUSD | EURUSD | GBPUSD | NZDUSD | USDCAD | USDJPY |
|---|---|---|---|---|---|---|
| **AUDUSD** | 1.0000 | 0.7765 | 0.8056 | 0.8445 | 0.7490 | 0.7871 |
| **EURUSD** | | 1.0000 | 0.8692 | 0.7109 | 0.7513 | 0.7618 |
| **GBPUSD** | | | 1.0000 | 0.7606 | 0.8017 | 0.8410 |
| **NZDUSD** | | | | 1.0000 | 0.6747 | 0.7458 |
| **USDCAD** | | | | | 1.0000 | 0.7503 |
| **USDJPY** | | | | | | 1.0000 |

**Table 2.12: Loadings of Global Factors derived by Principal Components (PC_level, PC_slope) on Each Currency Pair's Level and Slope**

| | AUDUSD | EURUSD | GBPUSD | NZDUSD | USDCAD | USDJPY |
|---|---|---|---|---|---|---|
| **PC_level** | 0.41 | 0.39 | 0.41 | 0.40 | 0.40 | 0.40 |
| **PC_slope** | 0.40 | 0.41 | 0.42 | 0.39 | 0.39 | 0.40 |

**Table 2.13: Cumulative Proportion of Variance and Correlation**

The left column records the proportion of variance of PC_level and PC_slope of all currency pairs' levels and slopes, respectively. The right column records the correlation between principal components and calculated factors in equation (2.13) and (2.14), corr(PC_level, GlobalLevel) and corr (PC_slope, GlobalSlope), respectively.

| | **Proportion of Variance** | **Correlation with Global** |
|---|---|---|
| **PC_level** | 0.937 | 0.9998 |
| **PC_slope** | 0.8559 | 0.9992 |

**Table 2.14: Time Series Test**

The table sorts currencies by interest rate differential from low to high, regresses their returns $r_{p,t}$ on risk factors, and records pricing error $\alpha_p$, factor exposures $\beta_p$, and time series explanation power adjusted R-squared (Adj-R2). All values are annualized, with Newey-West standard error included in parenthesis. "., *, **, ***" indicate statistical significance at 10%, 5%, 1%, and 0.1% levels, respectively, by Newey and West (1987) and Andrews (1991).

**Panel a: Risk factors by Lustig et al. (2011)**

$$r_{p,t} = \alpha_p + \beta_{p,dol}DOL_t + \beta_{p,hml}HML_t + \epsilon_{p,t}$$

| 6 portfolios | I1 (lowest interest rate) | I2 | I3 | I4 | I5 | I6 (highest interest rate) |
|---|---|---|---|---|---|---|
| $\boldsymbol{\alpha_p}$ | 0.0201 | -0.0025 | -0.0202 | -0.0366. | 0.0192 | 0.0201 |
| | (0.0140) | (0.01261) | (0.0220) | (0.0201) | (0.0182) | (0.0140) |
| $\boldsymbol{\beta_{p,dol}}$ | 1.0262*** | 0.8881*** | 0.9262*** | 0.8987*** | 1.2346*** | 1.0262*** |
| | (0.0539) | (0.0845) | (0.1192) | (0.1056) | (0.0719) | (0.0539) |
| $\boldsymbol{\beta_{p,hml}}$ | -0.6227*** | -0.0064 | -0.0032 | 0.0660 | 0.1889*** | 0.3773*** |
| | (0.0359) | (0.0489) | (0.0452) | (0.0405) | (0.0426) | (0.0359) |
| **Adj-R2** | 0.8250 | 0.6241 | 0.6774 | 0.8676 | 0.8281 | 0.9253 |

| 3 portfolios | P1 (lowest interest rate) | P2 | P3 (highest interest rate) |
|---|---|---|---|
| $\boldsymbol{\alpha_p}$ | 0.0144. | -0.0288. | 0.0144. |
| | (0.0077) | (0.0154) | (0.0077) |
| $\boldsymbol{\beta_{p,dol}}$ | 1.0424*** | 0.9152*** | 1.0424*** |
| | (0.0211) | (0.0421) | (0.0211) |
| $\boldsymbol{\beta_{p,hml}}$ | -0.5196*** | 0.0391 | 0.4804*** |
| | (0.0164) | (0.0329) | (0.01644) |
| **Adj-R2** | 0.9366 | 0.8435 | 0.9829 |

**Panel b: Level factor by our paper**

$$r_{p,t} = \alpha_p + \beta_{p,dol}DOL_t + \beta_{p,level}Level_t + \epsilon_{p,t}$$

| 6 portfolios | I1 (lowest interest rate) | I2 | I3 | I4 | I5 | I6 (highest interest rate) |
|---|---|---|---|---|---|---|
| $\boldsymbol{\alpha_p}$ | -0.1247 | 0.0312 | 0.0761 | 0.0317 | -0.0571 | 0.0426 |
| | (0.1538) | (0.0323) | (0.0696) | (0.0614) | (0.0432) | (0.1126) |
| $\boldsymbol{\beta_{dol}}$ | 0.2894. | 0.8790*** | 0.9181*** | 0.9744*** | 1.4636*** | 1.4756*** |
| | (0.1486) | (0.0619) | (0.1182) | (0.0858) | (0.0795) | (0.0752) |
| $\boldsymbol{\beta_{level}}$ | 1.2192 | -0.2893 | -0.8238 | -0.5831 | 0.6582 | -0.1816 |
| | (1.4841) | (0.2882) | (0.5326) | (0.5412) | (0.4069) | (0.9356) |
| **Adj-R2** | 0.0685 | 0.6249 | 0.5831 | 0.6735 | 0.8377 | 0.8043 |

| 3 portfolios | P1 (lowest interest rate) | P2 | P3 (highest interest rate) |
|---|---|---|---|
| $\boldsymbol{\alpha_p}$ | -0.0467 | 0.0539 | -0.0072 |
| | (0.0647) | (0.0331) | (0.0642) |
| $\boldsymbol{\beta_{p,dol}}$ | 0.5842*** | 0.9462*** | 1.4696*** |
| | (0.0657) | (0.0368) | (0.0663) |

| | | | |
|---|---|---|---|
| $\boldsymbol{\beta_{p,level}}$ | 0.4652 | -0.7034** | 0.2383 |
| | (0.5785) | (0.2655) | (0.5622) |
| **Adj-R2** | 0.5086 | 0.8482 | 0.8832 |

**Panel c: Slope factor by our paper**

$$r_{p,t} = \alpha_p + \beta_{p,dol}DOL_t + \beta_{p,slope}Slope_t + \epsilon_{p,t}$$

| **6 portfolios** | **I1 (lowest interest rate)** | **I2** | **I3** | **I4** | **I5** | **I6 (highest interest rate)** |
|---|---|---|---|---|---|---|
| $\boldsymbol{\alpha_p}$ | 0.0337 | -0.0093 | -0.0200 | -0.0374. | 0.0176 | 0.0155 |
| | (0.0404) | (0.0100) | (0.0228) | (0.0196) | (0.0179) | (0.0228) |
| $\boldsymbol{\beta_{p,dol}}$ | 0.3190* | 0.8650*** | 0.9229*** | 0.9751*** | 1.4549*** | 1.4631*** |
| | (0.1328) | (0.0536) | (0.1147) | (0.0909) | (0.0745) | (0.0878) |
| $\boldsymbol{\beta_{p,slope}}$ | -2.7648. | 1.1872*** | -0.0356 | 0.1814 | 0.4026 | 1.0292 |
| | (1.6576) | (0.3095) | (0.8879) | (0.6550) | (0.6490) | (0.6237) |
| **Adj-R2** | 0.105 | 0.6333 | 0.5769 | 0.6705 | 0.8359 | 0.8073 |

| **3 portfolios** | **P1 (lowest interest rate)** | **P2** | **P3 (highest interest rate)** |
|---|---|---|---|
| $\boldsymbol{\alpha_p}$ | 0.0120 | -0.0287* | 0.0165 |
| | (0.0190) | (0.0141) | (0.0146) |
| $\boldsymbol{\beta_{p,dol}}$ | 0.5920*** | 0.9490*** | 1.4590*** |
| | (0.0633) | (0.0387) | (0.0658) |
| $\boldsymbol{\beta_{p,slope}}$ | -0.7888 | 0.0729 | 0.7159 |
| | (0.7137) | (0.6152) | (0.4456) |
| **Adj-R2** | 0.5119 | 0.8421 | 0.8846 |

**Table 2.15: Cross-sectional Test**

The table summarizes prices of risk factors $\lambda$ (and parameter b in the GMM test), and cross-sectional explanation power adjusted R-squared (Adj-R2). All values are annualized, with Newey-West standard error included in parenthesis. "., *, **, ***" indicate statistical significance at 10%, 5%, 1%, and 0.1% levels, respectively, by Newey and West (1987) and Andrews (1991).

**Panel a: Risk factors by Lustig et al. (2011)**

FMB: $r_p = \widehat{\beta_{p,dol}}\lambda_{dol} + \widehat{\beta_{p,hml}}\lambda_{hml} + \epsilon_p$

GMM: $E[(1 - b_{dol}(DOL_t - \mu_{dol}) - b_{hml}(HML_t - \mu_{hml}))r_{p,t}] = 0, \lambda = \Omega_{DOL,HML}b$

| | 6 portfolios | | 3 portfolios | |
|---|---|---|---|---|
| | **FMB** | **GMM** | **FMB** | **GMM** |
| $\boldsymbol{\lambda_{dol}}$ | 0.0286. | 0.0185 | 0.0140 | 0.0323 |
| | (0.0107) | (0.0314) | (0.0067) | (0.0350) |
| $\boldsymbol{b_{dol}}$ | | 0.2016 | | 0.2223 |
| | | (0.4011) | | (0.3830) |
| $\boldsymbol{\lambda_{hml}}$ | 0.0290 | 0.0173 | 0.0167 | 0.0393 |
| | (0.0223) | (0.0648) | (0.0235) | (0.0503) |
| $\boldsymbol{b_{hml}}$ | | -0.0202 | | 0.0990 |
| | | (0.2238) | | (0.3084) |
| **Adj-R2** | 0.4850 | -0.3153 | 0.1063 | -0.9696 |

**Panel b: Level factor by our paper**

FMB: $r_p = \widehat{\beta_{p,dol}}\lambda_{dol} + \widehat{\beta_{p,level}}\lambda_{level} + \epsilon_p$

GMM: $E[(1 - b_{dol}(DOL_t - \mu_{dol}) - b_{hml}(Level_t - \mu_{hml}))r_{p,t}] = 0, \lambda = \Omega_{DOL,Level}b$

| | 6 portfolios | | 3 portfolios | |
|---|---|---|---|---|
| | **FMB** | **GMM** | **FMB** | **GMM** |
| $\boldsymbol{\lambda_{dol}}$ | 0.0299** | 0.0352 | 0.0148* | 0.0287 |
| | (0.0059) | | (0.0048) | |
| $\boldsymbol{b_{dol}}$ | | 0.4534 | | 0.4331 |
| | | (0.3200) | | (0.3850) |
| $\boldsymbol{\lambda_{level}}$ | 0.0232* | 0.0296 | 0.0185** | 0.0404 |
| | (0.0051) | | (0.0026) | |
| $\boldsymbol{b_{level}}$ | | 0.2177** | | 0.2971 |
| | | (0.0841) | | (0.1931) |
| **Adj-R2** | 0.7758 | 0.4378 | 0.2123 | 0.6681 |

**Panel c. Slope factor by our paper**

FMB: $r_p = \alpha + \widehat{\beta_{p,dol}}\lambda_{dol} + \widehat{\beta_{p,slope}}\lambda_{slope} + \epsilon_p$

GMM: $E[(1 - b_{dol}(DOL_t - \mu_{dol}) - b_{slope}(Slope_t - \mu_{slope}))r_{p,t}] = 0, \lambda = \Omega_{DOL,Slope}b$

| | 6 portfolios | | 3 portfolios | |
|---|---|---|---|---|

| | FMB | GMM | FMB | GMM |
|---|---|---|---|---|
| $\boldsymbol{\lambda_{dol}}$ | 0.0293* | 0.0199 | 0.0141 | 0.0758 |
| | (0.0105) | (0.0295) | (0.0067) | (0.0737) |
| $\boldsymbol{b_{dol}}$ | | 0.2276 | | 0.1709 |
| | | (0.3683) | | (0.5811) |
| | | | | |
| $\boldsymbol{\lambda_{slope}}$ | -0.0030 | -0.0021 | 0.0027 | 0.0362 |
| | (0.0018) | (0.0119) | (0.0120) | (0.0502) |
| $\boldsymbol{b_{slope}}$ | | -2.8226 | | 42.5747 |
| | | (14.4777) | | (63.2816) |
| | | | | |
| **Adj-R2** | 0.5018 | -0.2352 | 0.0254 | -16.8975 |

**Table 2.16: Performance of HML factor in literature**

Lustig et al. (2011) uses data from 35 countries (15 developed countries) from November 1983 to December 2009. Della Corte et al. (2016) uses data from 20 countries (10 developed countries) from January 1998 to December 2013.

| | | Lustig et al. (2011) | | Della Corte et al. (2016) | |
|---|---|---|---|---|---|
| | | **35 countries** | **15 Developed countries** | **20 countries** | **10 Developed countries** |
| **GMM** | $\lambda_{dol}$ | 0.0040 | 0.0307 | 0.02 | 0.02 |
| | | (0.0177) | (0.0205) | | |
| | $b_{dol}$ | 0.0004 | 0.0032 | | |
| | | (0.0031) | (0.0022) | | |
| | $\lambda_{HML}$ | 0.0551 | 0.3391 | -0.04 | -0.07 |
| | | (0.0214) | (0.0252) | | |
| | $b_{HML}$ | 0.0057 | 0.0035 | | |
| | | (0.0022) | (0.0022) | | |
| | **Adj-R2** | 0.4125 | -0.5565 | 0.19 | 0.16 |
| **FMB** | $\lambda_{dol}$ | 0.0134 | 0.0190 | 0.02 | 0.02 |
| | | (0.0135) | (0.0173) | | |
| | $\lambda_{HML}$ | 0.0550* | 0.0329 | -0.07 | -0.10 |
| | | (0.0179) | (0.0191) | | |
| | **Adj-R2** | 0.7011 | 0.6478 | 0.24 | 0.19 |

**Table 2.17: Beta Sorting (36-month window)**

The table summarizes statistics of excess returns for portfolios sorted by level beta (Panel a) and slope beta (Panel b), respectively, including the mean, standard deviation (St. dev.), skewness, kurtosis, Sharpe ratio (SR), auto-correlation coefficient of degree one (AC(1)), and sample size (Obs). All values are annualized. "., *, **, ***" indicate statistical significance at 10%, 5%, 1%, and 0.1% levels, respectively, by Newey and West (1987) and Andrews (1991). Panel a sorts currencies by level beta from low to high and calculates level spread by longing currencies of the highest beta and shorting ones of the lowest beta. Panel b sorts currencies by the slope beta from low to high and calculates slope spread by shorting currencies of the highest beta and longing ones of the lowest beta.

**a. level**

| 6 portfolios | I1 (lowest beta, short) | I2 | I3 | I4 | I5 | I6 (highest beta, long) | Level |
|---|---|---|---|---|---|---|---|
| **Mean** | -0.0411 | -0.0295 | -0.0201 | 0.0375 | 0.0399 | 0.0467 | 0.0878* |
| **St. dev.** | 0.1099 | 0.1317 | 0.1198 | 0.1227 | 0.1102 | 0.1168 | 0.1177 |
| **Skew** | -0.4890 | -1.6295 | -1.6734 | -0.9297 | -0.3313 | 0.8964 | 0.9897 |
| **Kurt** | 4.2942 | 6.8830 | 9.6827 | 5.6487 | 5.0755 | 6.8907 | 4.8977 |
| **SR** | -0.3743 | -0.2240 | -0.1678 | 0.3056 | 0.3620 | 0.3999 | 0.7460 |
| **AC(1)** | 0.084 | 0.361 | -0.049 | 0.252 | 0.069 | 0.127 | 0.193 |
| **Obs** | 70 | 70 | 70 | 70 | 70 | 70 | 70 |

| 3 portfolios | P1 (lowest beta, short) | P2 | P3 (highest beta, long) | Level |
|---|---|---|---|---|
| **Mean** | -0.0353 | 0.0087 | 0.0433 | 0.0786* |
| **St. dev.** | 0.1030 | 0.1108 | 0.0954 | 0.1101 |
| **Skew** | -1.1301 | -1.5372 | 0.8988 | 1.0159 |
| **Kurt** | 5.0194 | 9.5671 | 6.0073 | 4.2995 |
| **SR** | -0.3428 | 0.0785 | 0.4539 | 0.7135 |
| **AC(1)** | 0.285 | 0.132 | 0.017 | 0.285 |
| **Obs** | 70 | 70 | 70 | 70 |

**b. slope**

| 6 portfolios | I1 (lowest beta, long) | I2 | I3 | I4 | I5 | I6 (highest beta, short) | Slope |
|---|---|---|---|---|---|---|---|
| **Mean** | 0.1101 | 0.0346 | -0.0010 | -0.0477 | -0.0724 | 0.0097 | 0.1004 |
| **St. dev.** | 0.1171 | 0.1072 | 0.1169 | 0.1256 | 0.1215 | 0.1190 | 0.1636 |
| **Skew** | -0.0990 | 0.6335 | -0.7302 | -1.4924 | -1.5850 | -0.8964 | 0.9155 |
| **Kurt** | 5.3611 | 7.5297 | 5.9996 | 8.0217 | 6.8977 | 5.5003 | 7.2843 |
| **SR** | 0.9404 | 0.3231 | -0.0087 | -0.3802 | -0.5957 | 0.0817 | 0.6136 |
| **AC(1)** | 0.035 | 0.091 | -0.097 | 0.266 | 0.322 | 0.123 | 0.212 |
| **Obs** | 70 | 70 | 70 | 70 | 70 | 70 | 70 |

| 3 portfolios | P1 (lowest beta, long) | P2 | P3 (highest beta, short) | Slope |
|---|---|---|---|---|
| **Mean** | 0.0724 | -0.0244 | -0.0313 | 0.1037* |

| | | | | |
|---|---|---|---|---|
| **St. dev.** | 0.0955 | 0.1125 | 0.1012 | 0.1042 |
| **Skew** | 0.6281 | -1.4230 | -1.2014 | 1.1003 |
| **Kurt** | 5.9443 | 8.9221 | 5.3960 | 4.7830 |
| **SR** | 0.7579 | -0.2191 | -0.3094 | 0.9953 |
| **AC(1)** | 0.02 | 0.119 | 0.284 | 0.401 |
| **Obs** | 70 | 70 | 70 | 70 |

**Table 2.18: Beta Sorting (12-month window)**

The table summarizes statistics of excess returns for portfolios sorted by level beta (Panel a) and slope beta (Panel b), respectively, including the mean, standard deviation (St. dev.), skewness, kurtosis, Sharpe ratio (SR), auto-correlation coefficient of degree one (AC(1)), and sample size (Obs). All values are annualized. "., *, **, ***" indicate statistical significance at 10%, 5%, 1%, and 0.1% levels, respectively, by Newey and West (1987) and Andrews (1991). Panel a sorts currencies by level beta from low to high and calculates the level spread by longing currencies of the highest beta and shorting ones of the lowest beta. Panel b sorts currencies by slope beta from low to high and calculates slope spread by shorting currencies of the highest beta and longing ones of the lowest beta.

**a. level**

| 6 portfolios | I1 (lowest beta, short) | I2 | I3 | I4 | I5 | I6 (highest beta, long) | Level |
|---|---|---|---|---|---|---|---|
| **Mean** | -0.0310 | -0.0671 | 0.0567 | 0.0714 | 0.0599 | 0.1308 | 0.1618** |
| **St. dev.** | 0.1277 | 0.1174 | 0.1239 | 0.1262 | 0.0972 | 0.1311 | 0.1416 |
| **Skew** | -1.2425 | -0.6445 | -0.8598 | -0.1811 | 0.2108 | 0.2247 | 0.3774 |
| **Kurt** | 6.4403 | 3.6187 | 8.4407 | 6.3078 | 4.2466 | 4.6330 | 4.2009 |
| **SR** | -0.2427 | -0.5713 | 0.4578 | 0.5656 | 0.6159 | 0.9976 | 1.1422 |
| **AC(1)** | 0.148 | 0.251 | 0.042 | -0.001 | -0.059 | -0.03 | 0.141 |
| **Obs** | 94 | 94 | 94 | 94 | 94 | 94 | 94 |

| 3 portfolios | P1 (lowest beta, short) | P2 | P3 (highest beta, long) | Level |
|---|---|---|---|---|
| **Mean** | -0.0490 | 0.0640 | 0.0953 | 0.1444*** |
| **St. dev.** | 0.1072 | 0.1153 | 0.0988 | 0.1029 |
| **Skew** | -1.4008 | -0.5674 | -0.1159 | 0.6353 |
| **Kurt** | 6.5906 | 8.8006 | 3.7615 | 4.6924 |
| **SR** | -0.4574 | 0.5554 | 0.9650 | 1.4026 |
| **AC(1)** | 0.246 | 0.041 | -0.02 | 0.2 |
| **Obs** | 94 | 94 | 94 | 94 |

**b. slope**

| 6 portfolios | I1 (lowest beta, long) | I2 | I3 | I4 | I5 | I6 (highest beta, short) | Slope |
|---|---|---|---|---|---|---|---|
| **Mean** | 0.1444 | 0.0518 | 0.0529 | 0.0626 | -0.0463 | -0.0448 | 0.1891** |
| **St. dev.** | 0.1236 | 0.1072 | 0.1260 | 0.1184 | 0.1283 | 0.1221 | 0.1575 |
| **Skew** | 0.7194 | -0.2869 | -0.6085 | -1.0843 | -0.9711 | -0.3437 | 1.4067 |
| **Kurt** | 4.2677 | 6.0012 | 5.5792 | 11.3658 | 4.9385 | 4.3543 | 6.8531 |
| **SR** | 1.1684 | 0.4834 | 0.4202 | 0.5288 | -0.3612 | -0.3664 | 1.2012 |
| **AC(1)** | -0.065 | 0.12 | 0.005 | 0.016 | 0.067 | 0.18 | 0.182 |
| **Obs** | 94 | 94 | 94 | 94 | 94 | 94 | 94 |

| 3 portfolios | P1 (lowest beta, long) | P2 | P3 (highest beta, short) | Slope |
|---|---|---|---|---|
| **Mean** | 0.0981 | 0.0578 | -0.0456 | 0.1436*** |

| | | | | |
|---|---|---|---|---|
| **St. dev.** | 0.0992 | 0.1120 | 0.1071 | 0.1010 |
| **Skew** | 0.7301 | -0.9674 | -0.6971 | 1.1014 |
| **Kurt** | 4.7857 | 10.0060 | 3.9166 | 4.5364 |
| **SR** | 0.9886 | 0.5156 | -0.4251 | 1.4220 |
| **AC(1)** | -0.069 | 0.028 | 0.242 | 0.141 |
| **Obs** | 94 | 94 | 94 | 94 |

**Table 2.19: Covariance between Carry Trade Return and Global Risk Factors of Level and Slope**

The table sorts currencies by interest rate differential from low to high, constructs Carry Trade by longing currencies of the highest interest rate and shorting ones of the lowest interest rate and records exposures of these portfolios' returns to our global risk factors, level and slope. $r_{p,t}$ is the excess return by each portfolio. All values are annualized, with Newey-West standard error included in parenthesis. "., *, **, ***" indicate statistical significance at 10%, 5%, 1%, and 0.1% levels, respectively, by Newey and West (1987) and Andrews (1991). Panels a and b report exposures to level and slope factors, respectively.

**a. Level**

$$r_{p,t} = \alpha_p + \beta_{p,level} Level_t + \epsilon_{p,t}$$

| 6 portfolios | I1 (lowest interest rate) | I2 | I3 | I4 | I5 | I6 (highest interest rate) | Carry |
|---|---|---|---|---|---|---|---|
| $\boldsymbol{\beta_{p,level}}$ | 1.1029 | -0.6438 | -1.1940 | -0.9760 | 1.1029 | -0.7767 | -1.8797 |
| | (1.2852) | (1.1434) | (1.3334) | (0.8993) | (1.2852) | (2.1003) | (2.8937) |

| 3 portfolios | P1 (lowest interest rate) | P2 | P3 (highest interest rate) | Carry |
|---|---|---|---|---|
| $\boldsymbol{\beta_{p,level}}$ | 0.2296 | -1.0850 | -0.3544 | -0.5840 |
| | (0.5145) | (0.9805) | (1.8082) | (1.7222) |

**b. Slope**

$$r_{p,t} = \alpha_p + \beta_{p,slope} Slope_t + \epsilon_{p,t}$$

| 6 portfolios | I1 (lowest interest rate) | I2 | I3 | I4 | I5 | I6 (highest interest rate) | Carry |
|---|---|---|---|---|---|---|---|
| $\boldsymbol{\beta_{p,slope}}$ | -2.2506 | 2.5814* | 1.4519 | 1.7531 | 2.7475* | 3.3874 | 5.6380. |
| | (1.4877) | (1.1055) | (1.4990) | (1.5604) | (1.3723) | (2.0832) | (3.3953) |

| 3 portfolios | P1 (lowest interest rate) | P2 | P3 (highest interest rate) | Carry |
|---|---|---|---|---|
| $\boldsymbol{\beta_{p,slope}}$ | 0.1654 | 1.6025 | 3.0675. | 2.9021 |
| | (0.4530) | (1.5171) | (1.7472) | (1.9132) |

# Chapter 3. EXPLORING MACROECONOMIC CONNECTIONS TO THE FX RISK TERM STRUCTURE

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## 3.1 INTRODUCTION

From a theoretical viewpoint, the nominal exchange rate is an important driver of aggregate fluctuations and a key link between international goods and asset markets. Structural DSGE frameworks aim an understanding of how policies or the intrinsic shocks in one country spill over into other countries via the exchange rates. However, structural models often have difficulties matching the exchange rate dynamics observed in the data. The estimation efforts of such general equilibrium models typically find fluctuations in nominal exchange rates to be unrelated to macroeconomic forces, and there has been a consensus in literature that exchange rates are empirically "disconnected" from fundamentals at the short to medium horizons (Meese and Rogoff, 1993; Evans and Lyons, 2002; Engel, 2014). This exchange rate disconnect manifests itself into various empirical puzzles, as generated by the behavior of post-Bretton Woods floating exchange rates, and each puzzle has its own vast literature exploring different reasons behind exchange rate fluctuations (Engel, 2014).

A related empirical anomaly that has received considerable attention in the literature is the uncovered interest parity (UIP) puzzle. To a first-order approximation -- ignoring variance and covariance risk, the UIP as a no-arbitrage condition implies that a country with high relative interest rates should expect to experience subsequent currency depreciation, ensuring zero expected excess returns from cross-border financial investments. Since Fama (1984), data consistently show significant and robust positive returns from "Carry Trade" strategies that invest in the currency with higher interest rates, an empirical regularity known as the forward-premium puzzle or the UIP puzzle. There have been numerous attempts to solve the forward discount puzzle, though as pointed out in Itskhoki and Mukhin (2017), any proposed solutions must also account for the high volatilities present in the exchange rates but absent in other macroeconomic variables.

There are two recent alternative approaches to explain these puzzles: 1) direct shocks to the exchange rate or international risking-sharing condition, which emphasizes an unpredictable contemporaneous shock; and 2) macroeconomic volatility shocks that induce time-varying risks in the exchange rates, which emphasizes the risk premium that can be priced and captured by people's expectations. The latter hypothesis has endogenous reaction to macro fundamentals, while the former hypothesis is related to financial shocks which are not specifically endogenous to macro observables. This chapter will empirically explore which set of variables dominate.

To achieve this exploration, instead of looking at currency returns where people commonly find macro disconnect, this chapter looks at FX risk term structure which is found able to proxy for the currency risk premia as shown in my chapters 1 and 2. The efforts to seek connections between macroeconomic variables and financial market risk premia are common in the asset pricing literature (van Binsbergen and Koijen, 2017; Ludvigson and Ng, 2009; Duffee, 2008; Piazzesi and Swanson, 2004; Ang and Piazzesi, 2003; Chen et al., 1986; Campbell, 1996). For example, Ludvigson and Ng (2009) empirically study the link between macroeconomic fundamentals and risk premia in bond markets and find that macroeconomic factors of real production and inflation have predictive power in the U.S. bond risk premia. Piazzesi and Swanson (2004) find that the growth of nonfarm payroll employment is able to predict excess returns on federal funds futures contract rates. In equity markets, numerous risk factors have been found to explain the stock excess returns since the work by Fama and French (1973). Chen et al. (1986) find that innovations in macroeconomic variables are risks priced in the stock market, and efforts are still going on to explore what is priced in these risk factors (van Binsbergen and Koijen, 2017). As shown in my chapters 1 and 2, the FX risk term structure is found able to explain the risk premia and return dynamics in the currency market. Therefore, we will follow this strand in the asset pricing literature to continue the effort in the currency market, investigating the connection between macroeconomic variables and the time-varying risks captured by the FX risk term structure.

For our methodology, we first follow the monetary policy literature, which uses vector autoregression models (VAR) to measure the effects of monetary policy shocks on macroeconomic variables (Christiano et al., 2000; Gertler and Karadi, 2015). We first follow the traditional literature to choose a small set of observable macroeconomic variables. In equity and fixed-income markets, there is some implication for the link between risk term structure and macroeconomic events of inflation, output, and policy uncertainties. Creal and Wu (2014) find that common movement in short-term interest rate volatilities is highly correlated with monetary policy, inflation, and GDP uncertainties. Bansal and Shaliastovich (2013) found that nominal bond risk premia and term premia are high when there is high inflation volatility and low when there is high real volatility. In the FX market, classic structural models imply that a currency pair is related to the money supply ratio, real income ratio, short-term interest rate differential, and trade balance difference of the two countries involved in the currency pair (Bilson, 1978 and 1979; Frenkel, 1976, 1979, and 1981; Dornbusch, 1976; Hooper and Morton, 1982). Though people did not find much empirical evidence relating these macroeconomic variables to exchange rates (Meese and Rogoff, 1983), our idea is to revisit the exploration of the possible macroeconomic connection through the channel of time-varying currency risks. More recently, Chen and Tsang (2013) also proposed the importance of variables of both countries involved in the currency pair. Therefore, we follow this literature to select a small set of observable macroeconomic variables, covering production, inflation, short-term interest rates, money supply, and trade balances of each country. Then we combine these macroeconomic variables together with FX risk term structures (level and slope) for a VAR analysis.

However, some macroeconomic driving sources are likely to be latent variables and are difficult to be summarized with a few observable series. Therefore, we next follow the recent literature of Jurado et al. (2015) and Ludvigson and Ng (2009) to explore information in a data-rich environment, utilizing 126 macroeconomic variables from the dataset in Jurado et al. (2015). The 126 macroeconomic series in this dataset are selected to represent broad categories of macroeconomic time series: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, and bond and stock market indexes. However, the high dimension VAR would substantially increase the complexity of estimation and analysis. Thus, we need to reduce the dimension at the same time to keep as much information as possible. Ludvigson and Ng (2009) use factor analysis to summarize the rich information from a large set of economic variables into a small number of estimated factors. Bernanke et al. (2005) and Kilian and Lütkepohl (2017) also propose a factor-augmented vector auto-regression (FAVAR) by a two-step method based on the estimation of principal component factors. Therefore, we will first extract a small number of factors from the large set of 126 macroeconomic series variables using principal component analysis and then combine these factors together with FX risk term structure variables (level and slope) for a VAR analysis. We find that shocks of income and output group variables can generate a clear and consistent impact pattern on FX risk term structure across different currency pairs. When there is a positive shock in the income and output group, there will be an instant positive impact on the FX risk level, and the impact gradually decreases to zero in the long run (beyond 10 months). Symmetrically, there will be an instant negative impact on the FX risk slope, and the impact gradually decreases to zero in the long run. Variables from other groups (e.g. housing, money, and credit) may also have some useful information, but their impacts are neither significant nor broadly systematic across different currency pairs. These findings may be supportive of the theory of connecting macroeconomic fundamentals to time-varying risks in the currency market.

In addition to the VAR, direct forecasting is a common approach in literature to investigate the link between macroeconomic activities and risk premia in financial markets (Ludvigson and Ng, 2009). Besides factor analysis, shrinkage methods to reduce the dimension of large datasets are also popular in recent empirical literature (Kim and Swanson, 2014; Bai and Ng, 2008). Therefore, we directly regress 126 macroeconomic series on the FX risk term structure and apply the machine learning technique of Least Absolute Shrinkage and Selection Operator (LASSO) for variable selection to investigate whether there are any informational and useful variables. Furthermore, we also know that these 126 macroeconomic variables are grouped into different categories, thus we apply the technique of group LASSO proposed by Friedman et al. (2010) to utilize this extra information for more robust estimation. Our group LASSO results show that variables among both financial groups and macroeconomic fundamentals are selected quite consistently across different currency pairs. These results may suggest that besides macroeconomic connection, financial co-movements also exist in currency markets, which is consistent with such findings in stock and bond markets. For example, Shiller and Beltratti (1992) find a correlation between asset prices in the stock and bond markets. Andersen et al. (2007) documented a simultaneous linkage across different financial markets and countries, controlling for macroeconomic fundamentals. This is also consistent with empirical evidence in bond markets, which finds bond risk premia forecastable by financial indicators (Fama and Bliss, 1987; Campbell and Shiller, 1991; Cochrane and Piazzesi, 2005).

## 3.2 Data, Method, and Main Results

### 3.2.1 *A Small Dataset and VAR*

(1) Data

In the FX market, classic structural models imply that a currency pair is related to a small set of key macroeconomic and international variables differenced between the two countries involved in the currency pair (Bilson, 1978 and 1979; Frenkel, 1976, 1979, and 1981; Dornbusch, 1976; Hooper and Morton, 1982). More recently, Chen and Tsang (2013) proposed the importance of variables of both countries involved in the currency pair. Meese and Rogoff (1983) summarized a general quasi-reduced form of exchange rate structural models, as shown in equation (3.1) below:

$$s = a_0 + a_1(m - m^*) + a_2(y - y^*) + a_3(r - r^*) + a_4(\pi - \pi^*)$$
$$+ a_5 TB + a_6 TB^* + \epsilon, \quad (3.1)$$

where $s$ is the log of the dollar price of the foreign currency, $m - m^*$ is the log of the money supply ratio between the U.S. and the foreign country, $y - y^*$ is the real income ratio between the U.S. and the foreign country, $r - r^*$ is the short-term interest rate differential between the U.S. and the foreign country, $\pi - \pi^*$ is the inflation differential between the U.S. and the foreign country, and $TB$ and $TB^*$ are the U.S. and foreign trade balances, respectively.

Though others have not found much empirical evidence relating these macroeconomic variables to exchange rates, our idea is to revisit the exploration of the possible macroeconomic connection through the channel of time-varying currency risks $\rho$, as shown in equation (3.2) below:

$$\rho = a_0 + a_1(m - m^*) + a_2(y - y^*) + a_3(r - r^*) + a_4(\pi - \pi^*)$$

$$+a_5 TB + a_6 TB^* + \epsilon, \quad (3.2)$$

where $\rho$ will be approximated by the FX risk term structure, level and slope, following the main findings of chapters 1 and 2. We follow this model setup to select a small set of key macroeconomic variables implied by structural currency models, covering production, inflation, short-term interest rates, money supply, and the trade balance of each country. Specifically, we use the industrial production index (IP), the consumer price index (CPI), the 3-month Libor rate (3m Libor), M3, and the current account balance (TB) from US Federal Reserve Bank at a quarterly frequency. All these data were transformed to ensure stationarity: IP, CPI, and M3 use log growth, the Libor rate uses the original level, and TB uses a growth percentage. We also checked that the FX risk term structure data (level and slope) are stationary.

(2) VAR

To explore the link between these macroeconomic variables and the FX risk term structure, we follow the monetary policy literature, which uses vector auto-regression models (VAR) to measure the effects of monetary policy shocks on macroeconomic variables (Christiano et al., 2000). We use the conventional empirical approach of VAR, following Gertler and Karadi (2015), to explore the interactions between the slope and level data of the FX risk term structure and macroeconomic variables of both countries involved in the currency pair. In order to do so, we combine the macroeconomic variables above and the FX slope and level series together for the VAR analysis, as shown in equation (3.3) below, where $Macro_{i,t}$ is a 10x1 vector of variables, following the same order as Jurado et al. (2015).

$$AY_{i,t} = CY_{i,t-1} + \epsilon_t \quad (3.3)$$

$$Y_{i,t} = [Level_{i,t}, Slope_{i,t}, Macro_{i,t}]'$$

$$Macro_{i,t}: m, m^*, y, y^*, r,\ r^*, \pi, \pi^*, TB, TB^*$$

$$i: AUDUSD, EURUSD, GBPUSD, NZDUSD, USDCAD, USDJPY$$

This VAR equation (3.3) is a structural form, where $\epsilon_t$ is orthogonal. We then can calculate impulse responses $\frac{\partial Y_t}{\partial \epsilon_{t-j}}$ to look at how the FX risk level and slope would change, when there is a shock from each of these key macroeconomic variables. The impulse response results are reported in Figure (3.1).

**Figure 3.1**

It is found that the shocks of both US industrial production growth and country-specific industrial production growth have clear impact patterns on FX risk term structure. When there is a unit of a positive shock in U.S. IP growth, levels of all the currencies tend to go down instantly, but the change will gradually drop back to zero in the long run. Simultaneously, the slopes of all the currencies tend to go up instantly, but the change will gradually go back to zero in the long run. However, when there is a unit of a positive shock in the country-specific IP growth, the level of that corresponding currency tends to go up. As suggested by chapter 2, a high level and negative slope indicate high risk. Therefore, one interpretation of the results is that a positive shock in U.S. IP growth helps reduce the risk for all currencies, while a positive shock in country-specific IP growth increases the risk for that corresponding currency. Besides IP, the shock of a country-specific short-term interest rate also generates a clear impact pattern on the FX risk term structure. When there is a unit of a positive shock in the country-specific short-term interest rate, the level tends to go up while the slope tends to go down for that corresponding currency. This may suggest that a positive shock in the country-specific short-term interest rate will increase the risk in that corresponding currency.

### 3.2.2 *A Large Dataset and Factor Analysis*

(1) Data

The literature traditionally only chooses a small set of observable macroeconomic variables; however, some macroeconomic driving sources are likely to be latent variables and are difficult to be summarized with a few observable series. Therefore, we follow Jurado et al. (2015) and Ludvigson and Ng (2009) to explore information in a data-rich environment by utilizing a large dataset of 132 macroeconomic variables from Jurado et al. (2015) at a monthly frequency from January 2000 to June 2012. The 132 macroeconomic series in this dataset are selected to represent broad categories of macroeconomic time series: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, and bond and stock market indexes. It is worth noticing that this set of variables includes not only pure macroeconomic variables but also financial market variables, whose common movements are likely to generate variation in cyclical real macroeconomic variables. The common movements in financial markets are also interesting to explore to see how they are related to the exchange rate market. However, we removed the five series on foreign exchange measures in the dataset, since they essentially serve as dependent variables in our exercise. So we have 126 series left from the original dataset. Following Jurado et al. (2015), the 126 series can be divided into eight groups:

- Group 1: Output and Income (17 series)
- Group 2: Labor Market (33 series)
- Group 3: Housing (10 series)
- Group 4: Consumption, Orders, and Inventories (14 series)
- Group 5: Money and Credit (10 series)
- Group 6: Bond (17 series)
- Group 7: Prices (21 series)
- Group 8: Stock Market (4 series)

All these data were transformed to ensure stationarity. A detailed description of the data and transformations is given in table (3.1).[30] Another reminder is that these data are all U.S. domestic since all the currencies are paired with U.S. dollars.

**Table 3.1**

(2) Principal Component Analysis

We have a large number of variables; however, the high dimension VAR would substantially increase the complexity of estimation and analysis. Now in a data-rich environment, we need to reduce the dimension but at the same time to keep as much information as possible. Ludvigson and Ng (2009) use factor analysis by principal component analysis (PCA) to summarize rich information from a large set of economic variables into a small number of estimated factors. The methodology of PCA is common in the macroeconomics literature (Stock and Watson 2002a, 2002b, 2004). Bernanke et al. (2005) and Kilian and Lütkepohl (2017) also propose a factor-augmented vector autoregression (FAVAR) by a two-step method based on the estimation of principal components factors. Therefore, we will first extract a small number of factors from the 132 macroeconomic series variables using principal component analysis before performing a VAR analysis.

For each group of the macroeconomic series variables (Group 1 to 8 as shown in section 3.2.1), the factors are constructed by the method of principal component analysis (PCA). The raw data (which are in different units) used to form factors are always transformed to achieve stationarity

[30] Please see the online data appendix of Jurado et al. (2015) for full definitions of these variables. We also report the information in table (3.1) here for readers' convenience.

and are standardized before performing PCA. We chose the first two factors (PC1 and PC2) in each group, which can cumulatively explain 50%-90% of the variation of all series within the group, as shown in Table (3.2). The loadings of PC1 and PC2 in each group are also listed in Table (3.3). The constructed factors can be then treated as proxies for each group and hence can be used in our subsequent VAR implementation.

**Table 3.2**

**Table 3.3**

(3) VAR with macroeconomic factors

We then use the conventional empirical approach of VAR, following Gertler and Karadi (2015), to explore the interactions between slope and level data of FX risk term structure and macroeconomic factors (principal components generated above). In order to do so, we combine the constructed macroeconomic factors and the FX slope and level series together into one "Macro-FX dataset" ready to use for VAR analysis, as shown in equation (3.4) below, where $PCfactor_{i,t}$ is a 16x1 vector of variables, following the same order as Jurado et al. (2015). *Global* is the common risk factor as extracted in chapter 2, calculated by taking the average of level and slope across all the currency pairs.

$$AY_{i,t} = CY_{i,t-1} + \epsilon_{i,t} \quad (3.4)$$

$$Y_{i,t} = [Level_{i,t}, Slope_{i,t}, PCfactor_t]'$$

$$PCfactor: PC1\ and\ PC2\ of\ each\ macro\ variable\ group$$

*i: AUDUSD, EURUSD, GBPUSD, NZDUSD, USDCAD, USDJPY, Global*

The VAR equation (3.4) is a structural form, where $\epsilon_t$ is orthogonal. We then can calculate impulse responses $\frac{\partial Y_t}{\partial \epsilon_{t-j}}$ to look at how the FX risk level and slope would change when there is a shock from each of these macroeconomic factors. The impulse responses results are reported in Figure (3.2).

**Figure 3.2**

We can find that shocks of the first factor (PC1) in the Output and Income group have significant impacts on both the slope and level of FX risk term structure, and the impact patterns are consistent across all currencies paired with USD. Specifically, when there is a unit of a positive shock of PC1 in the Output and Income group, the level will increase instantly, and the slope will decrease for all the currencies. Admittedly, these results are not easy to interpret because the factor PC1 is not an unobservable variable, constructed by PCA analysis instead. However, when we look at the loadings of this PC1 factor on all the variables in the Output and Income group, we find that all the loadings are negative, as shown in table (3.3). This indicates that a positive shock of PC1 implies negative ones among the Output and Income group. Thus, a negative shock in U.S. output and income will increase the risk for all the currencies paired with the U.S. dollar. This is actually consistent with the U.S. IP results and interpretations in section 3.2.1 above.

Factors from other groups may also have some useful information, but their impacts are not significant and also vary dramatically for different currencies. For example, the shock of the second factor (PC2) in the Housing group has a quite consistent impact pattern on the FX risk level across all the currencies, which shows a bump right after a small dip, though with a wide confidence interval. The shock of the second factor (PC2) in the Bond group also has a consistent impact pattern on the FX risk level for some currencies, which shows an instant bump. However, we did not find any macroeconomic variables in Group 4 (Consumption, Orders, and Inventories) or Group 8 (Stock Market) selected for any currency pair. These findings may support the theory of connecting fundamental macroeconomic variables, particularly the output and income group, to the time-varying risks in the currency market.

### 3.2.3 *Group LASSO Regression*

In addition to VAR, direct forecasting is a common approach in the literature to investigate the link between macroeconomic activities and risk premia in financial markets (Ludvigson and Ng, 2009). Besides factor analysis, there is a growing trend in recent empirical macroeconomics literature to utilize the machine learning technique of shrinkage methods to reduce dimension (Kim and Swanson, 2014; Bai and Ng, 2008). In this section, we introduce the Least Absolute Shrinkage and Selection Operator (LASSO) to address the large set of 126 macroeconomic variables. LASSO was initially introduced by Tibshirani (1996), which includes a penalized term in a regression to drop variables of little information. Bai and Ng (2008) applied this technique using macroeconomic time series data. In addition, we also know that these 126 macroeconomic variables are grouped into eight different categories, which actually provides more information. The group LASSO technique proposed by Friedman et al. (2010) can well utilize this group information, which provides more robust estimation. In this section, we directly regress the 126 macroeconomic series of the eight groups on FX risk term structure level and slope and apply the group LASSO technique for variable selection to investigate which variables are informational, as shown in equation (3.5) and (3.6) below, where $\beta$ is a vector of group coefficients, $||\beta|| = \sum_{j=1}^{8} |\beta_j|$, and the regularization term $\lambda$ is determined by cross validation.

$$Level_{i,t} = \alpha + \beta Macro_{i,t} + \epsilon_{i,t}, \min(\sum_{t}^{T} \epsilon_{i,t}^2 + \lambda||\beta||) \quad (3.5)$$

$$Slope_{i,t} = \alpha + \beta Macro_{i,t} + \epsilon_{i,t}, \min\left(\sum_{t}^{T} \epsilon_{i,t}^2 + \lambda\left||\beta|\right|\right) \quad (3.6)$$

$$Macro_{i,t}: 126\ macro\ series\ of\ the\ 8\ groups$$

As shown in table (3.4), for both level and slope factor regressions, variables among both financial groups and macroeconomic fundamentals are selected quite consistently across different currency pairs, including Output and Income, Labor, Housing, Consumption, Money, Bond, and Stock. These results may suggest that besides macroeconomic connection, financial co-movements also exist in currency markets, which is consistent with the literature in bond and stock markets where a financial indicator helps predict asset prices and returns (Shiller and Beltratti, 1992; Andersen et al., 2007; Frankel and Froot, 1990; Fama and Bliss, 1987; Campbell and Shiller, 1991; Cochrane and Piazzesi, 2005).

**Table 3.4**

## 3.3 Conclusions

The paper explores the connection between macroeconomic events and the FX risk term structure, the time-varying currency risks. We first select a small number of observable macroeconomic and international variables at a quarterly frequency, covering production, inflation, short-term interest rate, money supply, and the trade balance, of each country, as suggested by structural models in the exchange rate literature, following Meese and Rogoff (1983). Then we combine these macroeconomic variables together with FX risk term structure (level and slope) to perform a VAR analysis, following the monetary policy literature (Gertler and Karadi, 2015). It is found that shocks of both US industrial production growth and country-specific industrial production growth have clear impact patterns on FX risk term structure. When there is a unit of a positive shock in U.S. IP growth, levels of all the currencies tend to go down instantly, and slopes tend to go up instantly. However, when there is a unit of a positive shock in the country-specific IP growth, the level of that corresponding currency tends to go up. As suggested by chapter 2, high level and negative slope indicate high risk. Therefore, we can try to interpret the results as a positive shock in U.S. IP growth helps reduce the risk for all currencies, while a positive shock in country-specific IP growth will increase the risk for that corresponding currency.

Next, we use a large dataset of 126 macroeconomic series variables at a monthly frequency in Jurado et al. (2015), covering broad categories to incorporate rich information. We first reduce the dimension by extracting a small number of factors from these data by performing principal component analysis following Ludvigson and Ng (2009) and Bernanke et al. (2005). Then we combine these factors with FX risk term structure variables (level and slope) to perform a VAR analysis. We found that shocks of income and output group variables can generate a clear and consistent impact pattern on FX risk term structure across different currency pairs. When there is a unit of a positive shock of PC1 in the income and output group, there will be an instant positive impact on the FX risk level and an instant negative impact on FX risk slope. Since all the loadings of the PC1 factor on all the variables in the Output and Income group are negative, a positive shock of PC1 implies negative ones among the Output and Income group. Thus, a negative shock in U.S. output and income will increase the currency risk. This is consistent with the U.S. IP results and interpretations above. These results together may support the theory of time-varying currency risks for possible macroeconomic connections.

In addition to the VAR analysis, we also performed a direct regression, following Ludvigson and Ng (2009), to investigate the link between macroeconomic activities and currency risk. We regress 126 macroeconomic variables of the eight groups on FX risk term structure variables, level and slope, and then apply the group LASSO technique for variable selection to investigate which macroeconomic variables have useful information. We found that variables among both financial groups and macroeconomic fundamentals are selected quite consistently across different currency pairs, including Output and Income, Labor, Housing, Consumption, Money, Bond, and Stock. This result may suggest that in addition to macroeconomic connection, financial market co-movements also exist in currency markets, which is consistent with the empirical evidence in bond and equity markets (Shiller and Beltratti, 1992; Andersen et al., 2007).

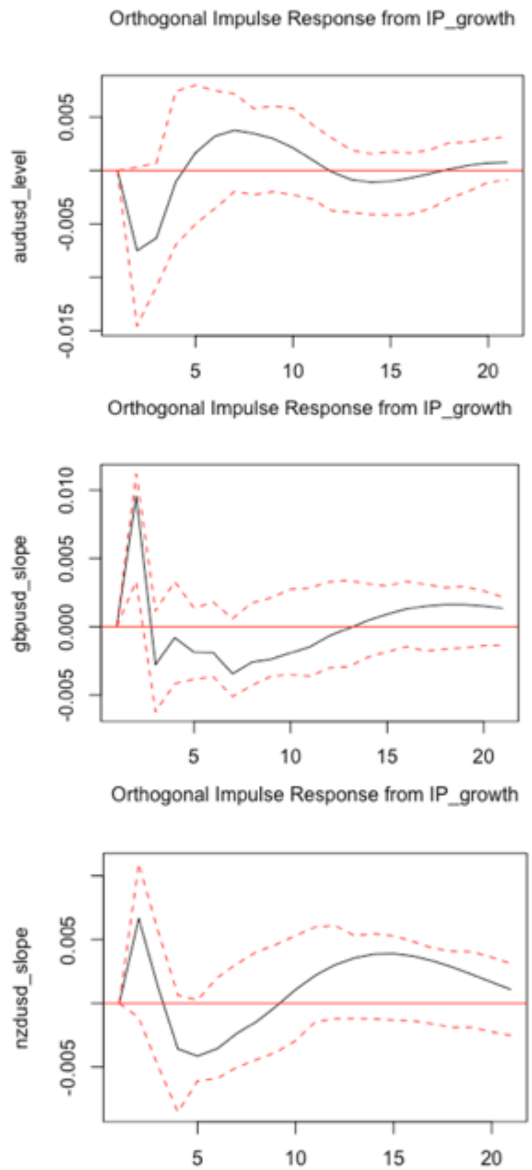
What we have done in this paper is a preliminary exploration of country-specific observable macroeconomic variables and a big search for U.S. data, which is just the beginning. For the next steps, we plan to explore a large dataset including commodity prices, international variables, and other country-specific variables. One of the data issues to solve is that many macroeconomic variables are monthly or even quarterly, while we have daily FX risk term structure variables. We need to think more about how to align frequencies and keep a sufficient sampling size. Besides data, there is also a high potential to further explore the methodology. For the VAR approach based on principal components, more careful studies are needed for interpretation. In addition to VAR, local projections by Jordà (2005) also provide an alternative to calculate impulse responses without specifying the dynamic multivariate functional system. Last but not the least, our findings that both macroeconomic connections and financial market co-movements exist in currency markets through the channel of currency risk premia, may suggest non-linear relationship and shed light on further theoretical exploration.

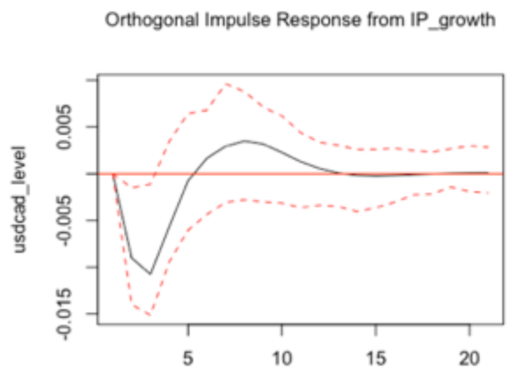
**Figure 3.1: Impulse Responses of FX Risk Term Structure to Macroeconomic Variables**

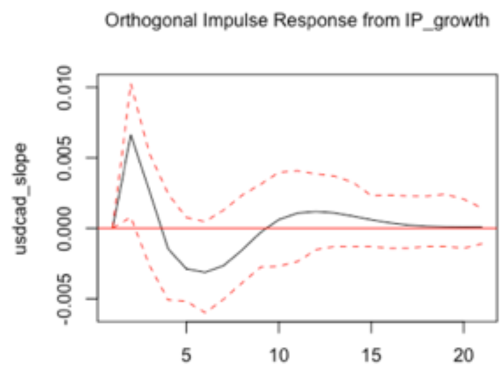
Dotted curves are upper and lower bounds of a 95% confidence interval constructed by bootstrapping. The unit of the horizontal axis is by quarter.

**a. IP**

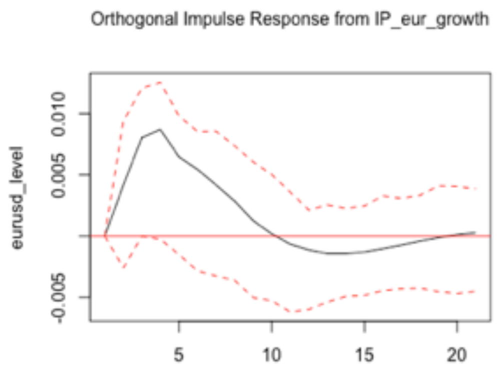
**(a1) U.S.**

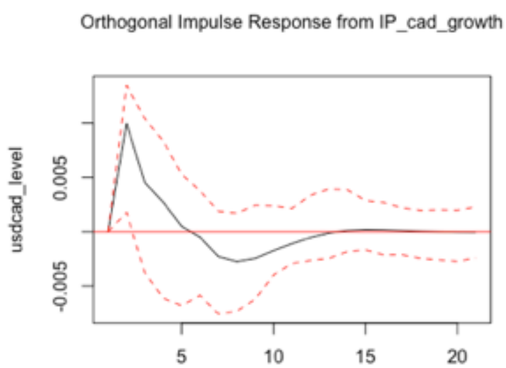




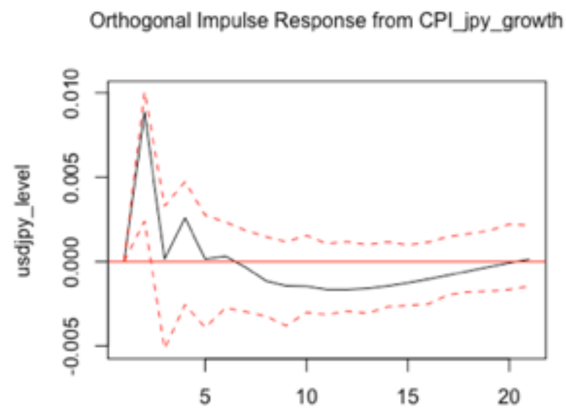



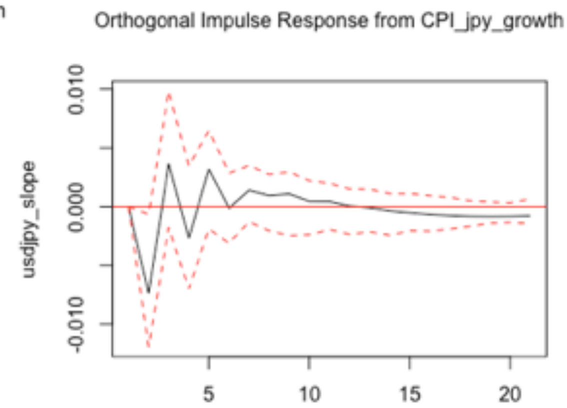

**(a2) Country-specific**



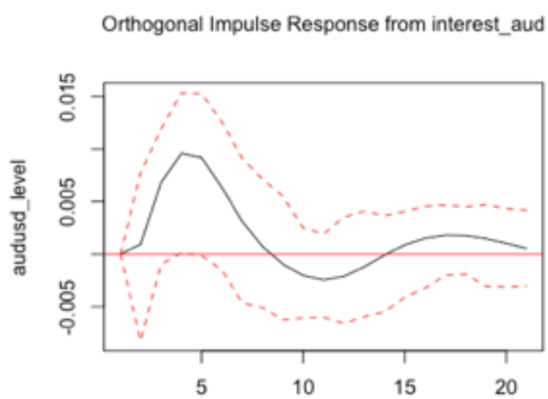



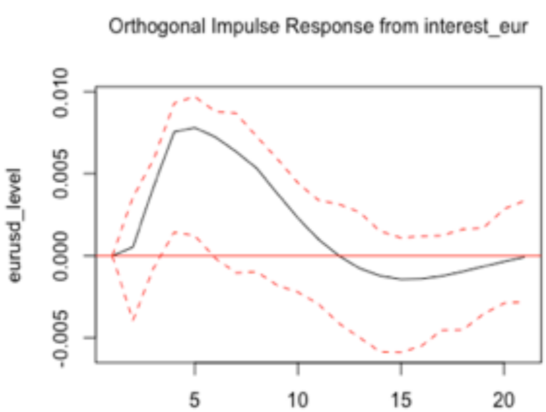
## b. CPI (country specific)

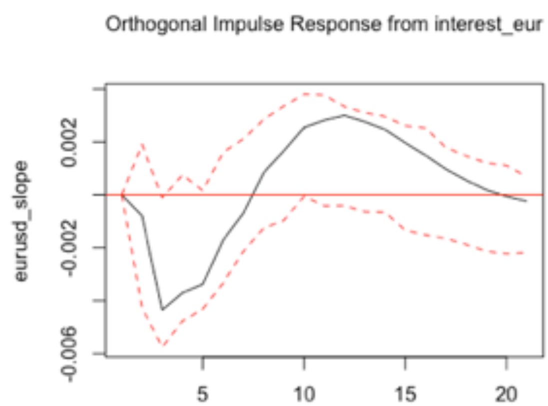


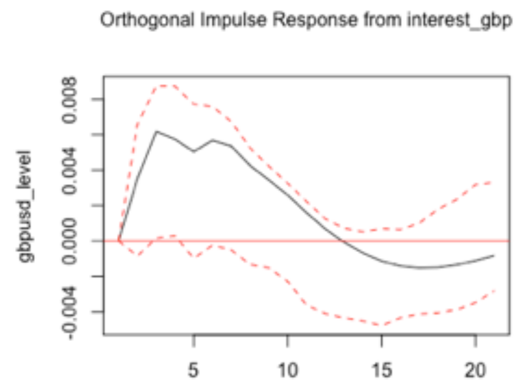



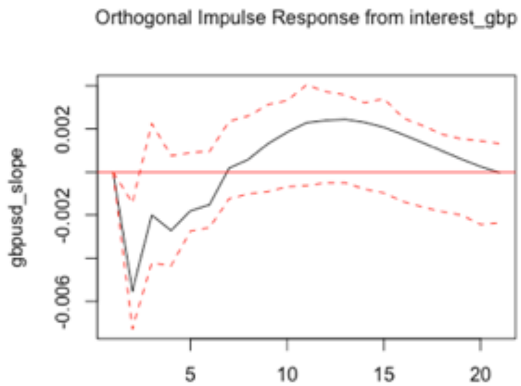

## c. Interest rate (country specific)




Orthogonal Impulse Response from interest_gbp
gbpusd_level
-0.004
0.000
0.004
0.008
5
10
15
20


Orthogonal Impulse Response from interest_gbp
gbpusd_slope
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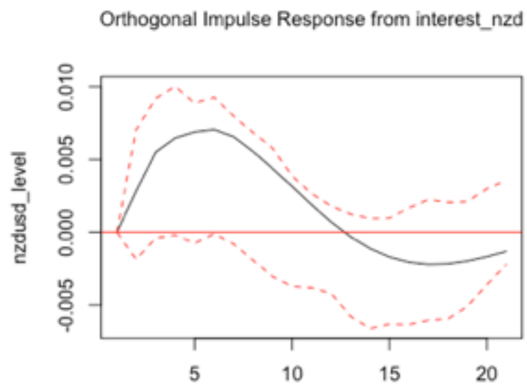
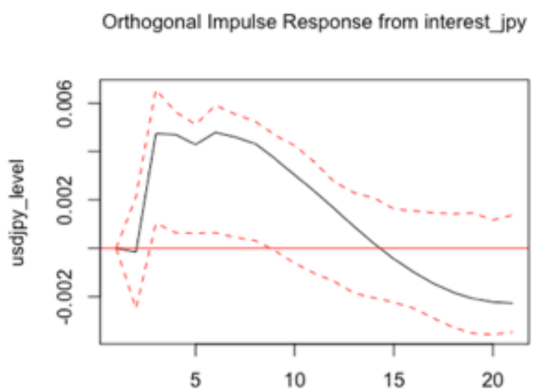
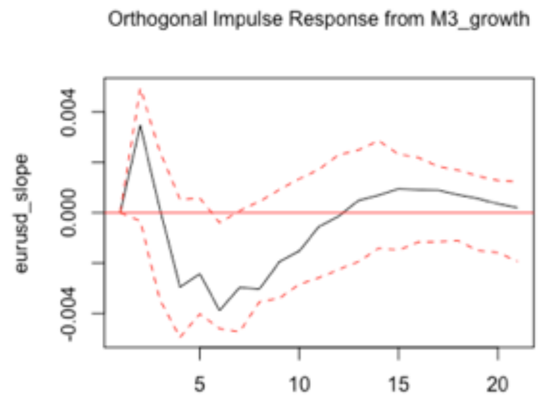
-0.002
0.002
5
10
15
20

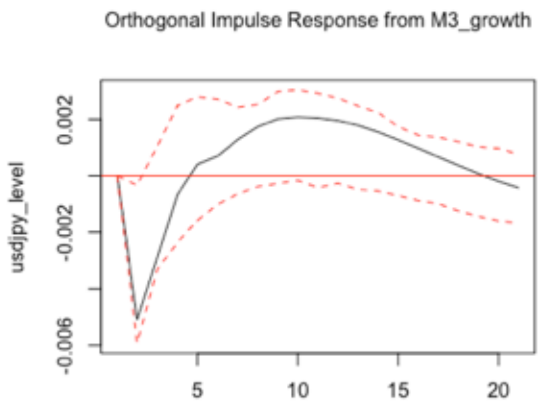

Orthogonal Impulse Response from interest_nzd
nzdusd_level
-0.005
0.000
0.005
0.010
5
10
15
20


Orthogonal Impulse Response from interest_jpy
usdjpy_level
-0.002
0.002
0.006
5
10
15
20

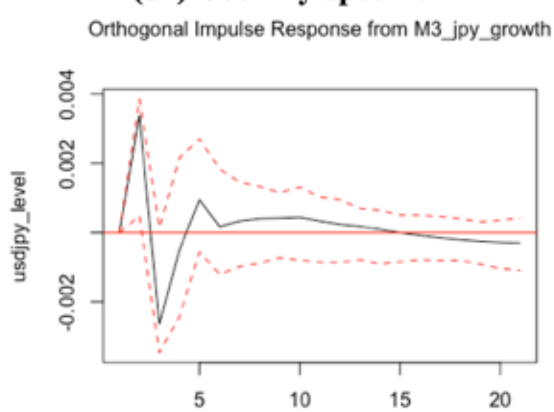
## d. Money supply

### (d1) U.S.



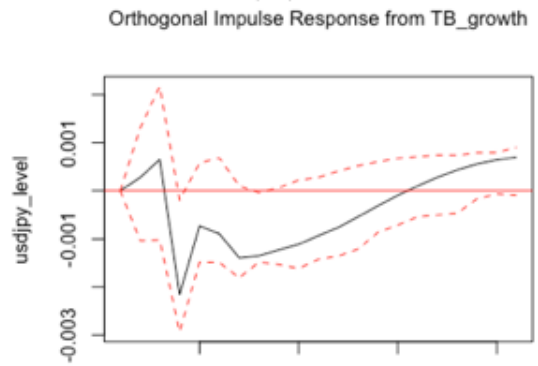




### (d2) Country-specific

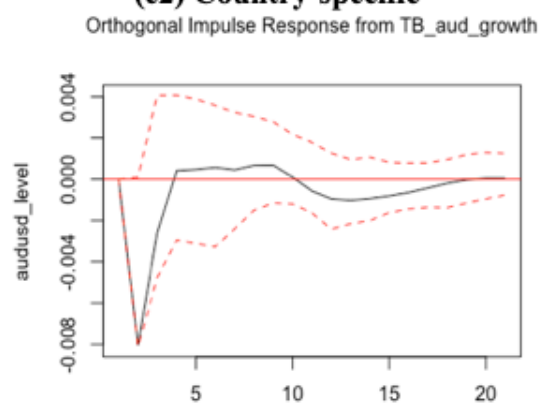


## e. Trade balance

### (e1) U.S.




### (e2) Country-specific



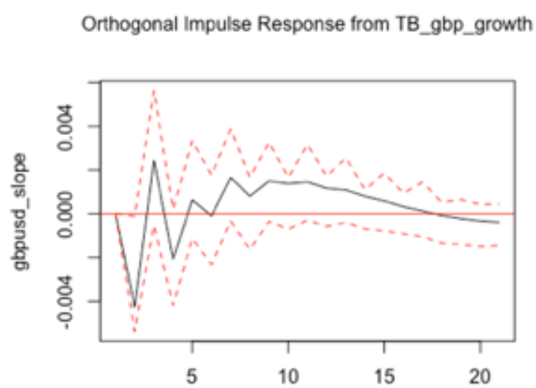
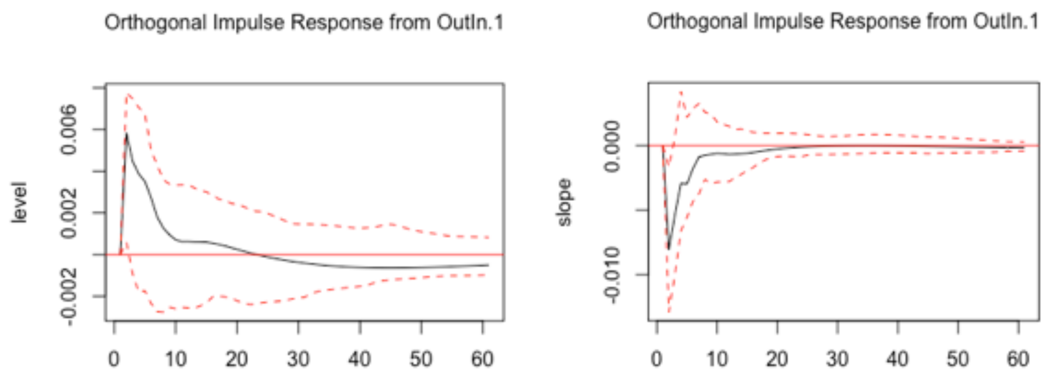



**Figure 3.2: Impulse Responses of FX Risk Term Structure to Macroeconomic Factors**

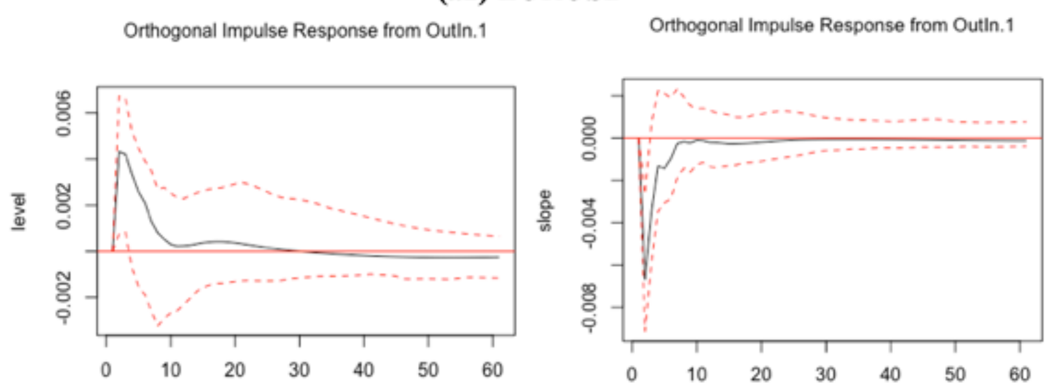
Dotted curves are upper and lower bounds of a 95% confidence interval constructed by bootstrapping.

**a. Group 1 – Output and Income**

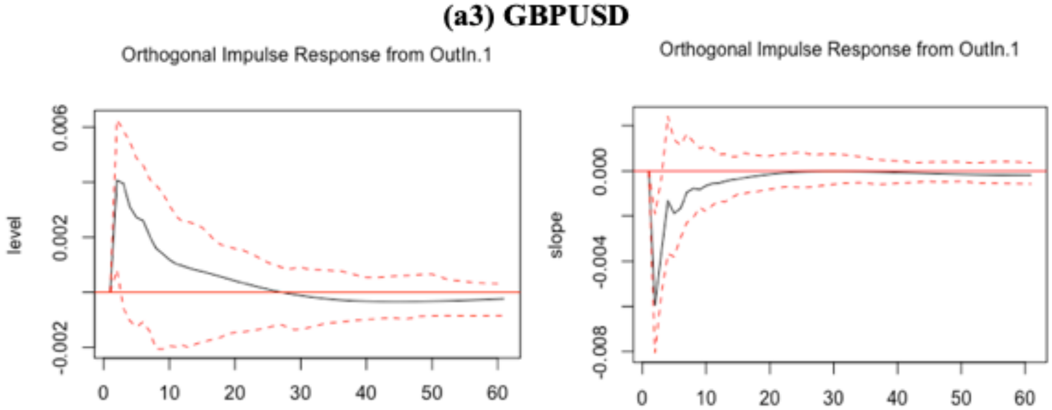
**(a1) AUDUSD**



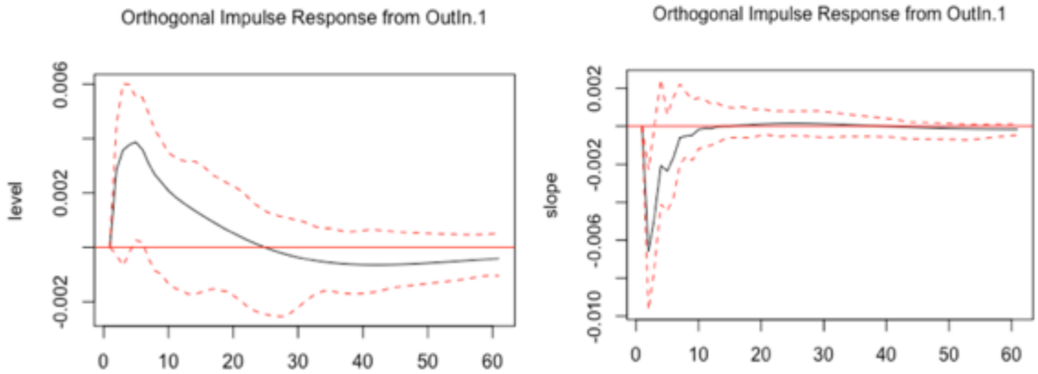

**(a2) EURUSD**



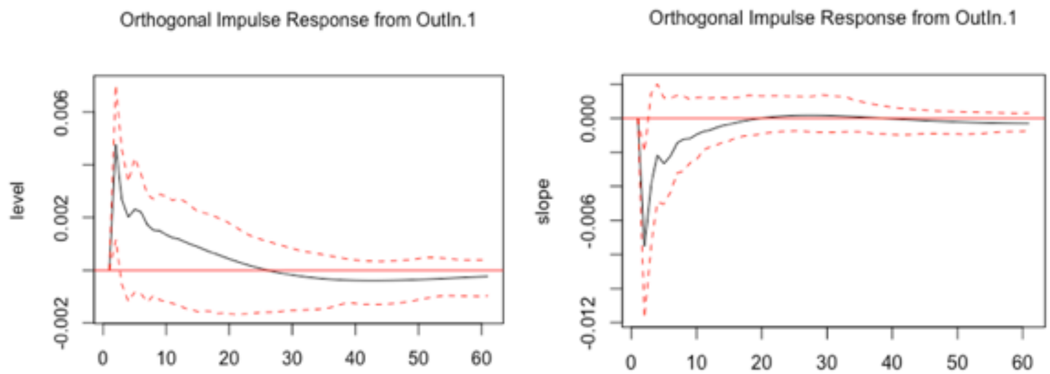

**(a3) GBPUSD**



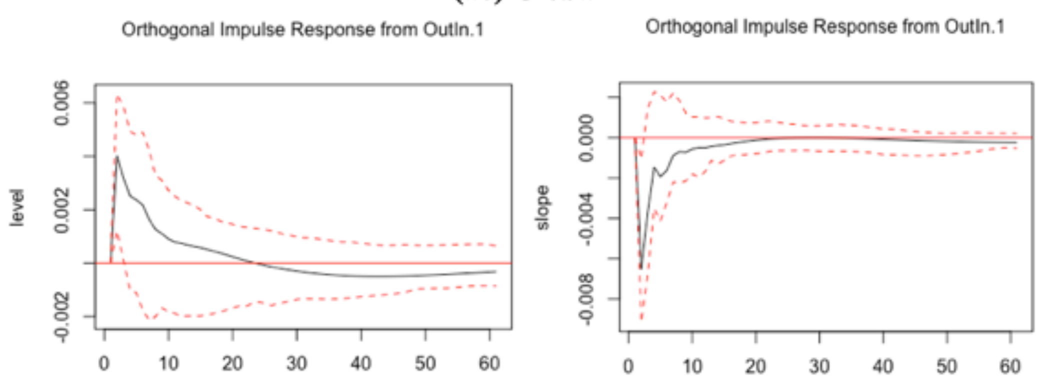
**(a4) USDCAD**




**(a5) USDJPY**

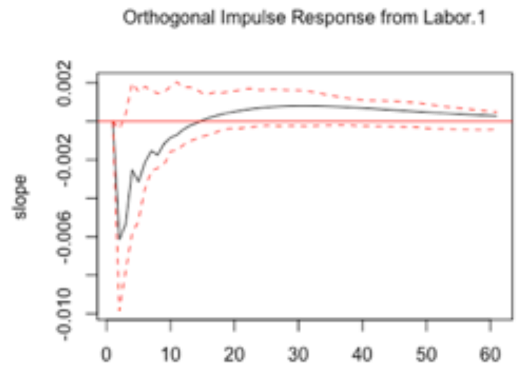



**(a6) Global**

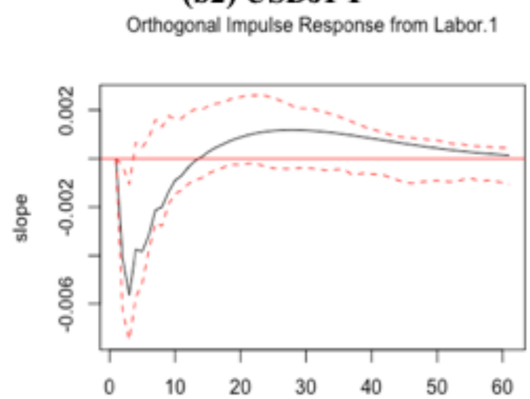


## b. Group 2 – Labor

### (b1) NZDUSD

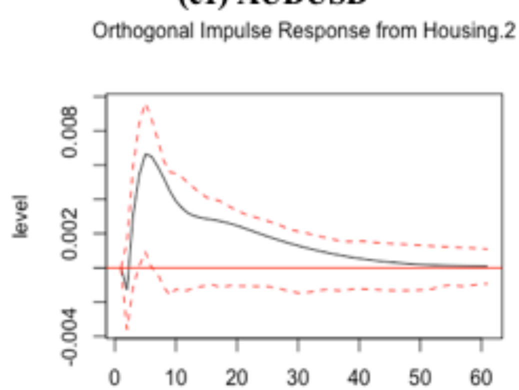



### (b2) USDJPY

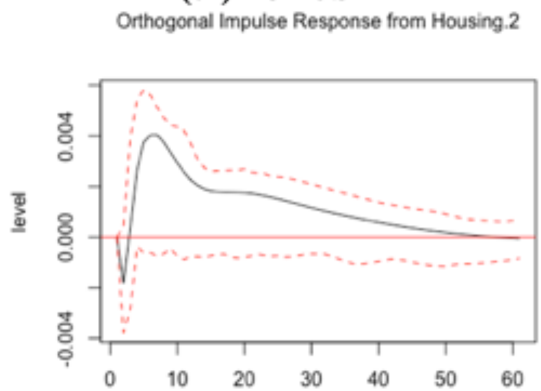



## c. Group 3 – Housing

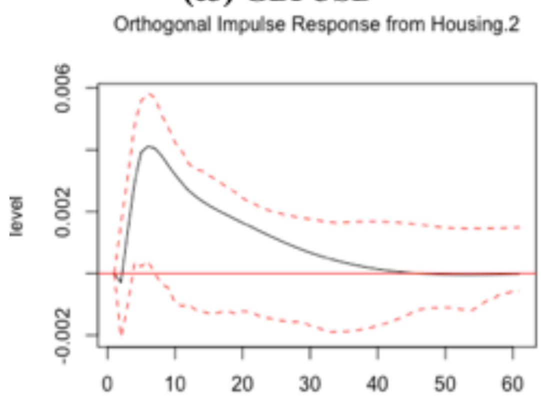
### (c1) AUDUSD



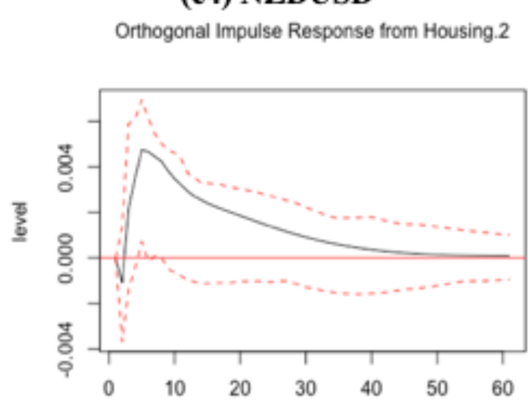
**(c2) EURUSD**



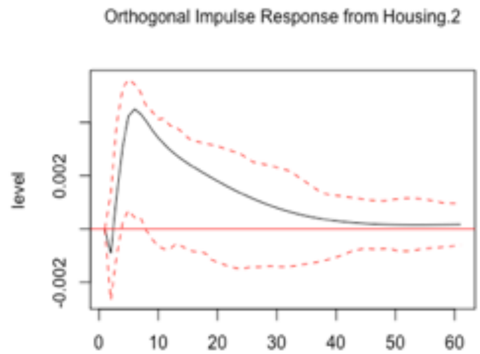

**(c3) GBPUSD**



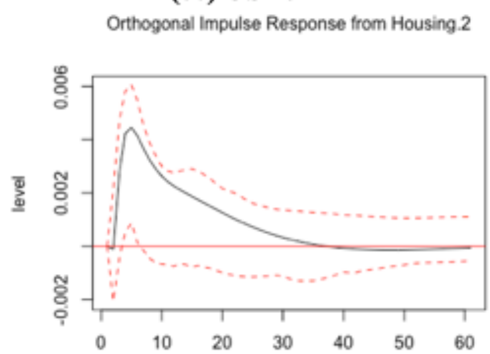

**(c4) NZDUSD**



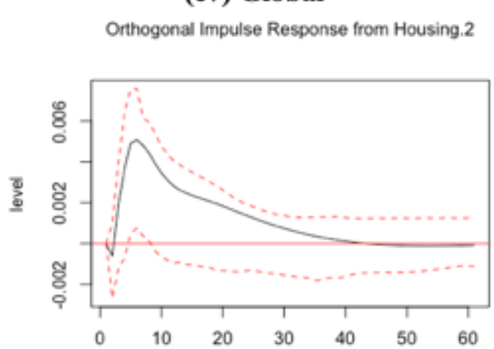
**(c5) USDCAD**




**(c6) USDJPY**

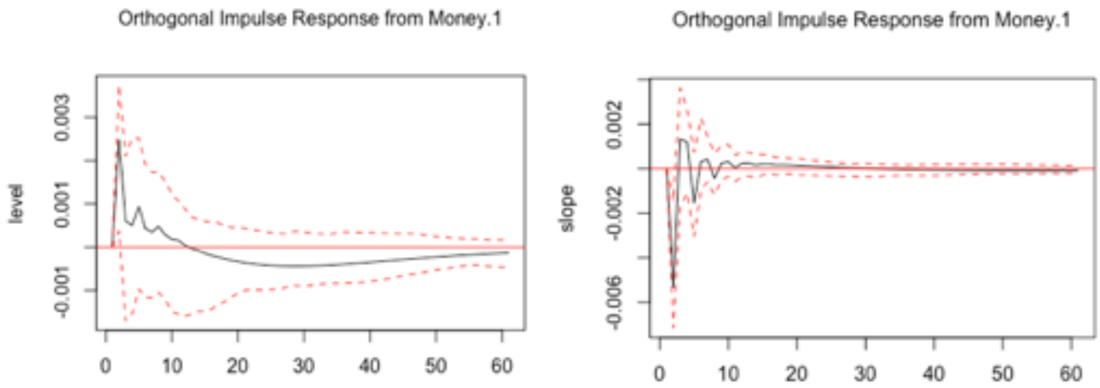



**(c7) Global**



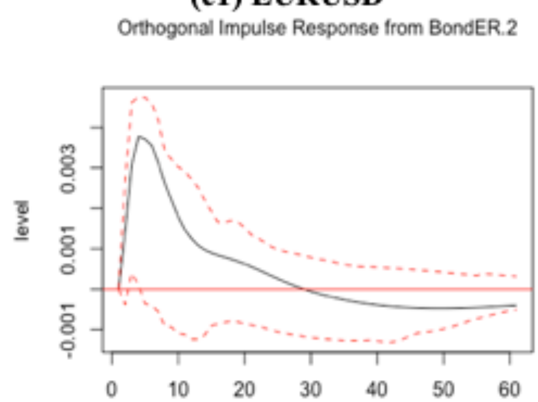
## d. Group 5 - Money and Credit

### USDCAD

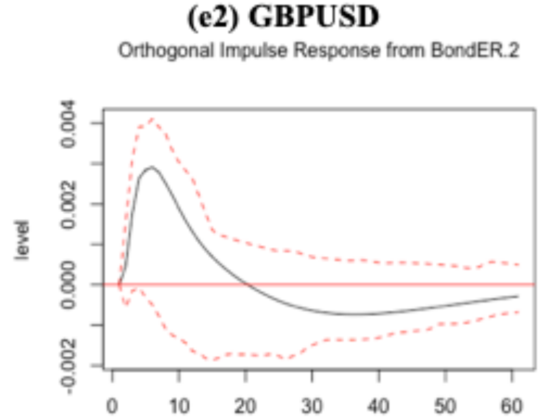



## e. Group 6 - Bond

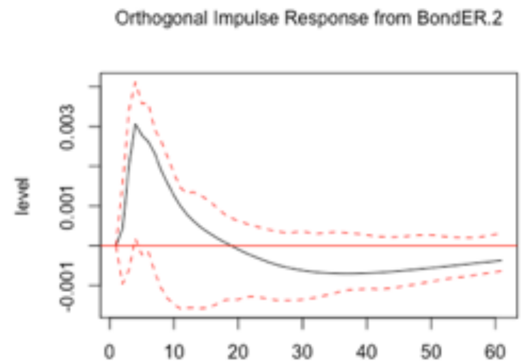
### (e1) EURUSD



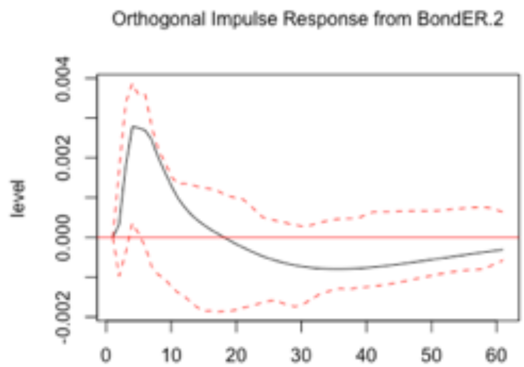

### (e2) GBPUSD



### (e3) NZDUSD

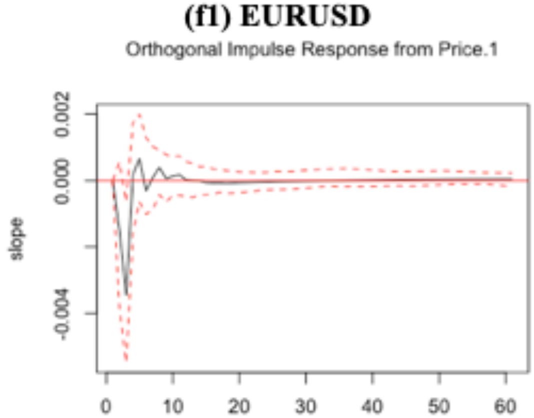



### (e4) Global

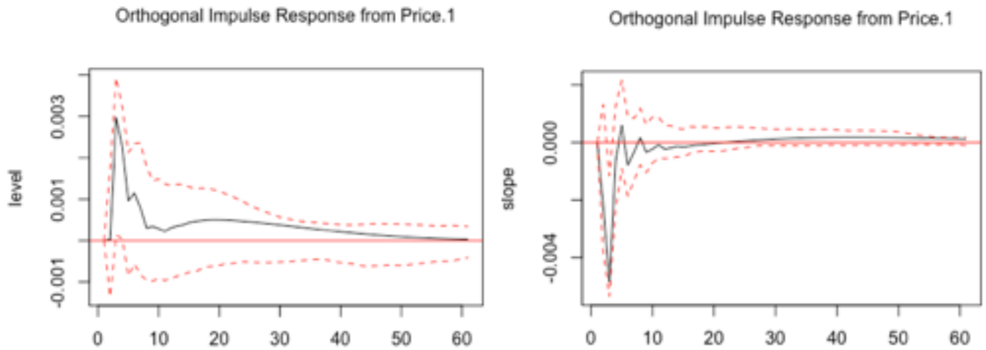



## f. Group 7-Prices

### (f1) EURUSD



**(f2) GBPUSD**




**(f3) Global**

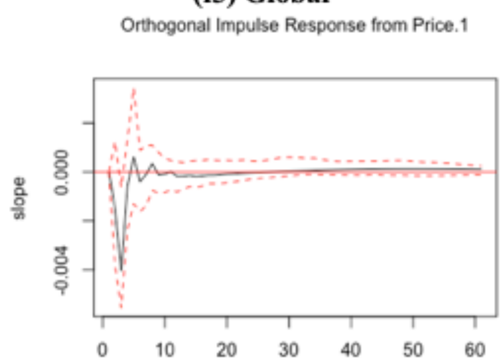


**Table 3.1: Data sources, Transformations, and Definitions**

Note: $ln$ means taking log, $lv$ means level (no transformation), $\Delta$ means difference, $\Delta^2$ means taking the difference twice.

| Series Number | Short Name | Transform | Description |
|---|---|---|---|
| | | **Group 1: Output and Income** | |
| 1 | PI | Δln | Personal Income (AR, Bil. Chain 2000 $) (TCB) |
| 2 | PI less transfers | Δln | Personal Income Less Transfer Payments (AR, Bil. Chain 2000 $) (TCB) |
| 6 | IP: total | Δln | Industrial Production Index - Total Index |
| 7 | IP: products | Δln | Industrial Production Index - Products, Total |
| 8 | IP: final prod | Δln | Industrial Production Index - Final Products |
| 9 | IP: cons gds | Δln | Industrial Production Index - Consumer Goods |
| 10 | IP: cons dble | Δln | Industrial Production Index - Durable Consumer Goods |
| 11 | IP: cons nondble | Δln | Industrial Production Index - Nondurable Consumer Goods |
| 12 | IP: bus eqpt | Δln | Industrial Production Index - Business Equipment |
| 13 | IP: matls | Δln | Industrial Production Index - Materials |
| 14 | IP: dble matls | Δln | Industrial Production Index - Durable Goods Materials |
| 15 | IP: nondble matls | Δln | Industrial Production Index - Nondurable Goods Materials |
| 16 | IP: mfg | Δln | Industrial Production Index - Manufacturing (Sic) |
| 17 | IP: res util | Δln | Industrial Production Index - Residential Utilities |
| 18 | IP: fuels | Δln | Industrial Production Index - Fuels |
| 19 | NAPM prodn | lv | Napm Production Index (Percent) |
| 20 | Cap util | Δlv | Capacity Utilization (Mfg.) (TCB) |

| | | **Group 2: Labor Market** | |
|---|---|---|---|
| 21 | Help wanted indx | Δlv | Index of Help-Wanted Advertising in Newspapers (1967=100;Sa) |
| 22 | Help wanted/emp | Δlv | Employment: Ratio; Help-Wanted Ads:No. Unemployed Clf |
| 23 | Emp CPS total | Δln | Civilian Labor Force: Employed, Total (Thous.,Sa) |
| 24 | Emp CPS nonag | Δln | Civilian Labor Force: Employed, Nonagric. Industries (Thous.,Sa) |
| 25 | U: all | Δlv | Unemployment Rate: All Workers, 16 Years & Over (%,Sa) |
| 26 | U: mean duration | Δlv | Unemploy. By Duration: Average (Mean) Duration in Weeks (Sa) |

| | | | |
|---|---|---|---|
| 27 | U<5wks | Δln | Unemploy. By Duration: Persons Unempl.Less than 5 Wks (Thous.,Sa) |
| 28 | U 5–14 wks | Δln | Unemploy. By Duration: Persons Unempl. 5 to 14 Wks (Thous.,Sa) |
| 29 | U 15+ wks | Δln | Unemploy. By Duration: Persons Unempl. 15 Wks + (Thous.,Sa) |
| 30 | U 15–26 wks | Δln | Unemploy. By Duration: Persons Unempl. 15 to 26 Wks (Thous.,Sa) |
| 31 | U 27+ wks | Δln | Unemploy. By Duration: Persons Unempl. 27 Wks + (Thous,Sa) |
| 32 | UI claims | Δln | Average Weekly Initial Claims, Unemploy. Insurance (Thous.) (TCB) |
| 33 | Emp: total | Δln | Employees on Nonfarm Payrolls: Total Private |
| 34 | Emp: gds prod | Δln | Employees on Nonfarm Payrolls - Goods-Producing |
| 35 | Emp: mining | Δln | Employees on Nonfarm Payrolls – Mining |
| 36 | Emp: const | Δln | Employees on Nonfarm Payrolls - Construction |
| 37 | Emp: mfg | Δln | Employees on Nonfarm Payrolls - Manufacturing |
| 38 | Emp: dble gds | Δln | Employees on Nonfarm Payrolls - Durable Goods |
| 39 | Emp: nondbles | Δln | Employees on Nonfarm Payrolls - Nondurable Goods |
| 40 | Emp: services | Δln | Employees on Nonfarm Payrolls - Service-Providing |
| 41 | Emp: TTU | Δln | Employees on Nonfarm Payrolls - Trade, Transportation, and Utilities |
| 42 | Emp: wholesale | Δln | Employees on Nonfarm Payrolls - Wholesale Trade |
| 43 | Emp: retail | Δln | Employees on Nonfarm Payrolls - Retail Trade |
| 44 | Emp: FIRE | Δln | Employees on Nonfarm Payrolls - Financial Activities |
| 45 | Emp: Govt | Δln | Employees on Nonfarm Payrolls - Government |
| 46 | Emp-hrs nonag | Δln | Employee Hours in Nonag. Establishments (AR, Bil. Hours) (TCB) |
| 47 | Avg hrs | lv | Avg Weekly Hrs of Prod or Nonsup Workers on Private Nonfarm Payrolls - Goods-Producing |
| 48 | Overtime: mfg | Δlv | Avg Weekly Hrs of Prod or Nonsup Workers on Private Nonfarm Payrolls - Mfg Overtime Hours |
| 49 | Avg hrs: mfg | lv | Average Weekly Hours, Mfg. (Hours) (TCB) |
| 50 | NAPM empl | lv | Napm Employment Index (Percent) |
| 129 | AHE: goods | $\Delta^2$ln | Avg Hourly Earnings of Prod or Nonsup Workers on Private Nonfarm Payrolls - Goods-Producing |

| | | | |
|---|---|---|---|
| 130 | AHE: const | $\Delta^2$ln | Avg Hourly Earnings of Prod or Nonsup Workers on Private Nonfarm Payrolls – Construction |
| 131 | AHE: mfg | $\Delta^2$ln | Avg Hourly Earnings of Prod or Nonsup Workers on Private Nonfarm Payrolls - Manufacturing |

**Group 3: Housing**

| | | | |
|---|---|---|---|
| 51 | Starts: nonfarm | ln | Housing Starts:Nonfarm(1947-58);Total Farm&Nonfarm(1959-) (Thous.,Saar) |
| 52 | Starts: NE | ln | Housing Starts:Northeast (Thous.U.)S.A. |
| 53 | Starts: MW | ln | Housing Starts:Midwest(Thous.U.)S.A. |
| 54 | Starts: South | ln | Housing Starts:South (Thous.U.)S.A. |
| 55 | Starts: West | ln | Housing Starts:West (Thous.U.)S.A. |
| 56 | BP: total | ln | Housing Authorized: Total New Priv Housing Units (Thous.,Saar) |
| 57 | BP: NE | ln | Houses Authorized by Build. Permits:Northeast (Thou.U.)S.A |
| 58 | BP: MW | ln | Houses Authorized by Build. Permits:Midwest (Thou.U.)S.A. |
| 59 | BP: South | ln | Houses Authorized by Build. Permits:South (Thou.U.)S.A. |
| 60 | BP: West | ln | Houses Authorized by Build. Permits:West (Thou.U.)S.A. |

**Group 4: Consumption, Orders, and Inventories**

| | | | |
|---|---|---|---|
| 61 | PMI | lv | Purchasing Managers' Index (Sa) |
| 62 | NAPM new ordrs | lv | Napm New Orders Index (Percent) |
| 63 | NAPM vendor del | lv | Napm Vendor Deliveries Index (Percent) |
| 64 | NAPM Invent | lv | Napm Inventories Index (Percent) |
| 65 | Orders: cons gds | Δln | Mfrs' New Orders, Consumer Goods and Materials (Bil. Chain 1982 $) (TCB) |
| 66 | Orders: dble gds | Δln | Mfrs' New Orders, Durable Goods Industries (Bil. Chain 2000 $) (TCB) |
| 67 | Orders: cap gds | Δln | Mfrs' New Orders, Nondefense Capital Goods (Mil. Chain 1982 $) (TCB) |
| 68 | Unf orders: dble | Δln | Mfrs' Unfilled Orders, Durable Goods Indus. (Bil. Chain 2000 $) (TCB) |
| 69 | M&T invent | Δln | Manufacturing and Trade Inventories (Bil. Chain 2000 $) (TCB) |
| 70 | M&T invent/sales | Δlv | Ratio, Mfg. and Trade Inventories to Sales (Based on Chain 2000 $) (TCB) |
| 3 | Consumption | Δln | Real Consumption (AC) a0m224/gmdc (a0m224 is from TCB) |
| 4 | M&T sales | Δln | Manufacturing and Trade Sales (Mil. Chain 1996 $) (TCB) |

| | | | |
|---|---|---|---|
| 5 | Retail sales | $\Delta$ln | Sales of Retail Stores (Mil. Chain 2000 $) (TCB) |
| 132 | Consumer expect | $\Delta$lv | U. of Mich. Index of Consumer Expectations (Bcd-83) |

**Group 5: Money and Credit**

| | | | |
|---|---|---|---|
| 71 | M1 | $\Delta^2$ln | Money Stock: M1(Curr,Trav.Cks,Dem Dep,Other Ck'able Dep) (Bil$,Sa) |
| 72 | M2 | $\Delta^2$ln | Money Stock:M2(M1+O'nite Rps,Euro$,G/P&B/D Mmmfs&Sav&Sm Time Dep(Bil$,Sa) |
| 73 | M3 | $\Delta^2$ln | Money Stock: M3(M2+Lg Time Dep,Term Rp's&Inst Only Mmmfs) (Bil$,Sa) |
| 74 | M2 (real) | $\Delta$ln | Money Supply - M2 in 1996 Dollars (Bci) |
| 75 | MB | $\Delta^2$ln | Monetary Base, Adj. tor Reserve Requirement Changes (Mil$,Sa) |
| 76 | Reserves tot | $\Delta^2$ln | Depository Inst Reserves:Total, Adj. tor Reserve Req Chgs (Mil$,Sa) |
| 77 | Reserves nonbor | $\Delta^2$ln | Depository Inst Reserves:Nonborrowed,Adj. Res Req Chgs (Mil$,Sa) |
| 78 | C&I loans | $\Delta^2$ln | Commercial & Industrial Loans Oustanding in 1996 Dollars (Bci) |
| 79 | ΔC&I loans | lv | Wkly Rp Lg Com'l Banks:Net Change Com'l & Indus Loans (Bil$,Saar) |
| 80 | Cons credit | $\Delta^2$ln | Consumer Credit Outstanding – Nonrevolving (G19) |
| 81 | Inst cred/PI | $\Delta$lv | Ratio, Consumer Installment Credit to Personal Income (Pct.) (TCB) |

**Group 6: Bond**

| | | | |
|---|---|---|---|
| 86 | Fed Funds | $\Delta$lv | Interest Rate: Federal Funds (Effective) (% per Annum,Nsa) |
| 87 | Comm paper | $\Delta$lv | Cmmercial Paper Rate (AC) |
| 88 | 3 mo T-bill | $\Delta$lv | Interest Rate: U.S.Treasury Bills, Sec Mkt, 3-Mo. (% per Ann,Nsa) |
| 89 | 6 mo T-bill | $\Delta$lv | Interest Rate: U.S.Treasury Bills, Sec Mkt, 6-Mo. (% per Ann,Nsa) |
| 90 | 1 yr T-bond | $\Delta$lv | Interest Rate: U.S.Treasury Const Maturities, 1-Yr. (% per Ann,Nsa) |
| 91 | 5 yr T-bond | $\Delta$lv | Interest Rate: U.S.Treasury Const Maturities, 5-Yr. (% per Ann,Nsa) |
| 92 | 10 yr T-bond | $\Delta$lv | Interest Rate: U.S.Treasury Const Maturities, 10-Yr. (% per Ann,Nsa) |
| 93 | Aaa bond | $\Delta$lv | Bond Yield: Moody's Aaa Corporate (% per Annum) |
| 94 | Baa bond | $\Delta$lv | Bond Yield: Moody's Baa Corporate (% per Annum) |
| 95 | CP-FF spread | lv | cp90-fyff (AC) |

| | | | |
|---|---|---|---|
| 96 | 3 mo-FF spread | lv | fygm3-fyff (AC) |
| 97 | 6 mo-FF spread | lv | fygm6-fyff (AC) |
| 98 | 1 yr-FF spread | lv | fygt1-fyff (AC) |
| 99 | 5 yr-FF spread | lv | fygt5-fyff (AC) |
| 100 | 10 yr-FF spread | lv | fygt10-fyff (AC) |
| 101 | Aaa-FF spread | lv | fyaaac-fyff (AC) |
| 102 | Baa-FF spread | lv | fybaac-fyff (AC) |

**Group 7: Prices**

| | | | |
|---|---|---|---|
| 108 | PPI: fin gds | $\Delta^2$ln | Producer Price Index: Finished Goods (82=100,Sa) |
| 109 | PPI: cons gds | $\Delta^2$ln | Producer Price Index: Finished Consumer Goods (82=100,Sa) |
| 110 | PPI: int mat’ls | $\Delta^2$ln | Producer Price Index: Intermed Mat.Supplies & Components (82=100,Sa) |
| 111 | PPI: crude mat’ls | $\Delta^2$ln | Producer Price Index: Crude Materials (82=100,Sa) |
| 112 | Spot market price | $\Delta^2$ln | Spot market price index: bls & crb: all commodities (1967=100) |
| 113 | Sens mat’ls price | $\Delta^2$ln | Index Of Sensitive Materials Prices (1990=100) (Bci-99a) |
| 114 | NAPM com price | lv | Napm Commodity Prices Index (Percent) |
| 115 | CPI-U: all | $\Delta^2$ln | Cpi-U: All Items (82-84=100,Sa) |
| 116 | CPI-U: apparel | $\Delta^2$ln | Cpi-U: Apparel & Upkeep (82-84=100,Sa) |
| 117 | CPI-U: transp | $\Delta^2$ln | Cpi-U: Transportation (82-84=100,Sa) |
| 118 | CPI-U: medical | $\Delta^2$ln | Cpi-U: Medical Care (82-84=100,Sa) |
| 119 | CPI-U: comm. | $\Delta^2$ln | Cpi-U: Commodities (82-84=100,Sa) |
| 120 | CPI-U: dbles | $\Delta^2$ln | Cpi-U: Durables (82-84=100,Sa) |
| 121 | CPI-U: services | $\Delta^2$ln | Cpi-U: Services (82-84=100,Sa) |
| 122 | CPI-U: ex food | $\Delta^2$ln | Cpi-U: All Items Less Food (82-84=100,Sa) |
| 123 | CPI-U: ex shelter | $\Delta^2$ln | Cpi-U: All Items Less Shelter (82-84=100,Sa) |
| 124 | CPI-U: ex med | $\Delta^2$ln | Cpi-U: All Items Less Medical Care (82-84=100,Sa) |
| 125 | PCE defl | $\Delta^2$ln | Pce, Impl Pr Defl:Pce (1987=100) |
| 126 | PCE defl: dlbes | $\Delta^2$ln | Pce, Impl Pr Defl:Pce; Durables (1987=100) |
| 127 | PCE defl: nondble | $\Delta^2$ln | Pce, Impl Pr Defl:Pce; Nondurables (1996=100) |
| 128 | PCE defl: service | $\Delta^2$ln | Pce, Impl Pr Defl:Pce; Services (1987=100) |

**Group 8: Stock Market**

| | | | |
|---|---|---|---|
| 82 | S&P 500 | $\Delta$ln | S&P’s Common Stock Price Index: Composite (1941-43=10) |

| | | | |
|---|---|---|---|
| 83 | S&P: indust | Δln | S&P's Common Stock Price Index: Industrials (1941-43=10) |
| 84 | S&P div yield | Δlv | S&P's Composite Common Stock: Dividend Yield (% per Annum) |
| 85 | S&P PE ratio | Δln | S&P's Composite Common Stock: Price-Earnings Ratio (%,Nsa) |

**Table 3.2: Cumulative Proportion of Variance Explained by PCs in Each Group**

| | **PC1** | **PC2** |
|---|---|---|
| **Group 1** | 51.51% | 65.06% |
| **Group 2** | 44.65% | 52.75% |
| **Group 3** | 96.70% | 98.09% |
| **Group 4** | 34.08% | 50.94% |
| **Group 5** | 25.42% | 41.88% |
| **Group 6** | 40.07% | 64.70% |
| **Group 7** | 49.82% | 58.90% |
| **Group 8** | 82.05% | 98.12% |

**Table 3.3: Loadings of PC1 and PC2 in Each Group**

**a. Group 1: Output and Income**

| Loadings | PC1 | PC2 |
|---|---|---|
| PI | -0.120 | -0.188 |
| PI.less.transfers | -0.159 | -0.158 |
| IP..total | -0.324 | -0.024 |
| IP..products | -0.322 | 0.156 |
| IP..final.prod | -0.309 | 0.201 |
| IP..cons.gds | -0.251 | 0.371 |
| IP..cons.dble | -0.215 | 0.037 |
| IP..cons.nondble | -0.148 | 0.489 |
| IP..bus.eqpt | -0.252 | -0.076 |
| IP..matls | -0.278 | -0.165 |
| IP..dble.matls | -0.271 | -0.071 |
| IP..nondble.matls | -0.216 | -0.243 |
| IP..mfg | -0.326 | -0.115 |
| IP..res.util | -0.016 | 0.568 |
| IP..fuels | -0.080 | -0.218 |
| NAPM.prodn | -0.220 | -0.035 |
| Cap.util | -0.320 | -0.122 |

**b. Group 2: Labor Market**

| Loadings | PC1 | PC2 |
|---|---|---|
| Help.wanted.indx | -0.100 | -0.307 |
| Help.wanted.unemp | -0.129 | -0.363 |
| Emp.CPS.total | -0.192 | -0.152 |
| Emp.CPS.nonag | -0.188 | -0.152 |
| U..all | 0.187 | 0.169 |
| U..mean.duration | 0.049 | -0.334 |
| U...5.wks | 0.010 | 0.207 |
| U.5.14.wks | 0.064 | 0.241 |
| U.15..wks | 0.169 | -0.046 |
| U.15.26.wks | 0.106 | 0.080 |
| U.27..wks | 0.141 | -0.106 |
| UI.claims | 0.081 | 0.280 |
| Emp..total | -0.251 | 0.026 |
| Emp..gds.prod | -0.250 | 0.046 |
| Emp..mining | -0.196 | 0.214 |

| | | |
|---|---|---|
| Emp..const | -0.219 | 0.017 |
| Emp..mfg | -0.242 | 0.049 |
| Emp..dble.gds | -0.240 | 0.032 |
| Emp..nondbles | -0.210 | 0.104 |
| Emp..services | -0.226 | 0.018 |
| Emp..TTU | -0.238 | 0.007 |
| Emp..wholesale | -0.233 | 0.096 |
| Emp..retail | -0.214 | -0.061 |
| Emp..FIRE | -0.209 | -0.026 |
| Emp..Govt | -0.002 | 0.005 |
| Agg.wkly.hours | -0.207 | -0.027 |
| Avg.hrs | -0.175 | 0.273 |
| Overtime..mfg | -0.080 | -0.363 |
| Avg.hrs..mfg | -0.188 | 0.246 |
| NAPM.empl | -0.230 | 0.030 |
| AHE..goods | -0.020 | -0.074 |
| AHE..const | 0.0005 | 0.068 |
| AHE..mfg | -0.015 | -0.182 |

**c. Group 3: Housing**

| Loadings | PC1 | PC2 |
|---|---|---|
| Starts..nonfarm | -0.321 | -0.063 |
| Starts..NE | -0.304 | 0.776 |
| Starts..MW | -0.313 | -0.284 |
| Starts..South | -0.318 | -0.086 |
| Starts..West | -0.318 | -0.210 |
| BP..total | -0.321 | -0.056 |
| BP..NE | -0.310 | 0.420 |
| BP..MW | -0.318 | -0.238 |
| BP..South | -0.319 | -0.086 |
| BP..West | -0.319 | -0.133 |

**d. Group 4: Consumption, Orders, and Inventories**

| Loadings | PC1 | PC2 |
|---|---|---|
| Real.Consumption | -0.237 | -0.106 |
| M.T.sales | -0.344 | -0.323 |
| Retail.sales | -0.216 | -0.175 |
| PMI | -0.393 | 0.260 |

| | | |
|---|---|---|
| NAPM.new.ordrs | -0.360 | 0.132 |
| NAPM.vendor.del | -0.292 | 0.269 |
| NAPM.Invent | -0.274 | 0.348 |
| Orders..cons.gds | -0.276 | -0.321 |
| Orders..dble.gds | -0.245 | -0.224 |
| Orders..cap.gds | -0.176 | -0.119 |
| Unf.orders..dble | -0.216 | 0.076 |
| M.T.invent | -0.287 | 0.353 |
| M.T.invent.sales | 0.194 | 0.525 |
| Consumer.expect | 0.024 | 0.053 |

**e. Group 5: Money and Credit**

| Loadings | PC1 | PC2 |
|---|---|---|
| M1 | 0.240 | -0.513 |
| M2 | 0.400 | -0.443 |
| Currency | 0.343 | 0.218 |
| M2..real. | 0.224 | -0.503 |
| MB | 0.429 | 0.178 |
| Reserves.tot | 0.472 | 0.249 |
| C.I.loan.plus | 0.330 | 0.326 |
| DC.I.loans | 0.307 | 0.152 |
| Cons.credit | -0.005 | 0.009 |
| Inst.cred.PI | 0.071 | -0.131 |

**f. Group 6: Bond**

| Loadings | PC1 | PC2 |
|---|---|---|
| Fed.Funds | 0.222 | -0.238 |
| Comm.paper | 0.185 | -0.227 |
| X3.mo.T.bill | 0.284 | -0.215 |
| X6.mo.T.bill | 0.312 | -0.248 |
| X1.yr.T.bond | 0.309 | -0.249 |
| X5.yr.T.bond | 0.223 | -0.219 |
| X10.yr.T.bond | 0.180 | -0.202 |
| Aaa.bond | 0.090 | -0.156 |
| Baa.bond | -0.003 | -0.055 |
| CP.FF.spread | -0.001 | 0.204 |
| X3.mo.FF.spread | 0.343 | 0.068 |
| X6.mo.FF.spread | 0.341 | 0.103 |

| | | |
|---|---|---|
| X1.yr.FF.spread | 0.338 | 0.107 |
| X5.yr.FF.spread | 0.282 | 0.302 |
| X10.yr.FF.spread | 0.240 | 0.348 |
| Aaa.FF.spread | 0.199 | 0.392 |
| Baa.FF.spread | 0.165 | 0.415 |

**g. Group 7: Prices**

| Loadings | PC1 | PC2 |
|---|---|---|
| PPI..fin.gds | -0.256 | 0.234 |
| PPI..cons.gds | -0.256 | 0.229 |
| PPI..int.mat.ls | -0.250 | 0.289 |
| PPI..crude.mat.ls | -0.202 | 0.316 |
| Spot.market.price | -0.151 | 0.384 |
| PPI..nonferrous | -0.110 | 0.311 |
| NAPM.com.price | 0.037 | -0.015 |
| CPI.U..all | -0.300 | -0.134 |
| CPI.U..apparel | -0.006 | -0.011 |
| CPI.U..transp | -0.291 | -0.202 |
| CPI.U..medical | 0.035 | 0.159 |
| CPI.U..comm. | -0.293 | -0.211 |
| CPI.U..dbles | -0.076 | -0.224 |
| CPI.U..services | -0.072 | 0.343 |
| CPI.U..ex.food | -0.299 | -0.128 |
| CPI.U..ex.shelter | -0.296 | -0.171 |
| CPI.U..ex.med | -0.300 | -0.135 |
| PCE.defl | -0.293 | -0.086 |
| PCE.defl..dlbes | -0.124 | -0.051 |
| PCE.defl..nondble | -0.290 | -0.158 |
| PCE.defl..service | -0.069 | 0.265 |

**h. Group 8: Stock Market**

| Loadings | PC1 | PC2 |
|---|---|---|
| S.P.500 | -0.537 | 0.269 |
| S.P..indust | -0.534 | 0.260 |
| S.P.div.yield | 0.537 | -0.110 |
| S.P.PE.ratio | -0.372 | -0.921 |

**Table 3.4: Informational Variables Selected by Group LASSO**

**(a) Level**

| | | AUDUSD | EURUSD | GBPUSD | NZDUSD | USDCAD | USDJPY | GLOBAL |
|---|---|---|---|---|---|---|---|---|
| **Output and Income** | PI | 0.0000 | 0.1826 | 0.1980 | 0.0079 | 0.3414 | 0.2897 | 0.1684 |
| | PI less transfers | 0.0000 | -0.1422 | -0.1398 | -0.0015 | -0.3103 | -0.2413 | -0.1287 |
| | IP: total | 0.0000 | -0.1584 | 3.0288 | 0.0266 | 1.6489 | -3.3336 | 0.1569 |
| | IP: products | 0.0000 | 0.3677 | -1.7933 | 0.0359 | -0.3516 | 1.7471 | 0.0766 |
| | IP: final prod | 0.0000 | -1.6577 | -1.3778 | -0.1094 | -0.4312 | -0.8618 | -0.8770 |
| | IP: cons gds | 0.0000 | 1.0885 | -0.3462 | -0.1086 | 0.2862 | -0.1041 | 0.0094 |
| | IP: cons dble | 0.0000 | 0.0146 | 0.3124 | 0.0442 | 0.0320 | 0.2179 | 0.1542 |
| | IP: cons nondble | 0.0000 | 0.2431 | 1.4590 | 0.1637 | 0.1861 | 0.9785 | 0.6918 |
| | IP: bus eqpt | 0.0000 | 0.4428 | 0.4641 | 0.0386 | 0.2740 | 0.2992 | 0.2977 |
| | IP: matls | 0.0000 | 0.0620 | -1.5004 | -0.0258 | -0.7689 | 1.7370 | -0.0813 |
| | IP: dble matls | 0.0000 | 0.2062 | 0.3939 | 0.0517 | 0.4679 | 0.3571 | 0.3004 |
| | IP: nondble matls | 0.0000 | 0.0460 | 0.1369 | 0.0335 | 0.2432 | 0.0453 | 0.1193 |
| | IP: mfg | 0.0000 | -1.5152 | -2.9259 | -0.2678 | -3.2354 | -2.6568 | -1.8273 |
| | IP: res util | 0.0000 | -0.0342 | -0.0450 | -0.0047 | -0.0468 | -0.0436 | -0.0317 |
| | IP: fuels | 0.0000 | 0.0337 | 0.0618 | 0.0021 | 0.0150 | 0.0362 | 0.0241 |
| | NAPM prodn | 0.0000 | -0.0001 | -0.0003 | 0.0000 | -0.0002 | -0.0002 | -0.0001 |
| | Cap util | 0.0000 | 0.0129 | 0.0309 | 0.0016 | 0.0228 | 0.0225 | 0.0140 |
| **Labor Market** | Help wanted indx | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0001 | 0.0000 |
| | Help wanted/unemp | 0.0000 | 0.0000 | 0.0000 | -0.0056 | 0.0000 | -0.0039 | 0.0000 |
| | Emp CPS total | 0.0000 | 0.0000 | 0.0000 | 0.2274 | 0.0000 | 0.1155 | 0.0000 |
| | Emp CPS nonag | 0.0000 | 0.0000 | 0.0000 | -0.2691 | 0.0000 | -0.1686 | 0.0000 |
| | U: all | 0.0000 | 0.0000 | 0.0000 | -0.0015 | 0.0000 | -0.0003 | 0.0000 |
| | U: mean duration | 0.0000 | 0.0000 | 0.0000 | 0.0006 | 0.0000 | 0.0006 | 0.0000 |
| | U < 5 wks | 0.0000 | 0.0000 | 0.0000 | 0.0023 | 0.0000 | 0.0008 | 0.0000 |
| | U 5-14 wks | 0.0000 | 0.0000 | 0.0000 | 0.0031 | 0.0000 | 0.0067 | 0.0000 |
| | U 15+ wks | 0.0000 | 0.0000 | 0.0000 | -0.0452 | 0.0000 | -0.0445 | 0.0000 |
| | U 15-26 wks | 0.0000 | 0.0000 | 0.0000 | 0.0160 | 0.0000 | 0.0142 | 0.0000 |
| | U 27+ wks | 0.0000 | 0.0000 | 0.0000 | 0.0175 | 0.0000 | 0.0194 | 0.0000 |
| | UI claims | 0.0000 | 0.0000 | 0.0000 | 0.0083 | 0.0000 | 0.0113 | 0.0000 |
| | Emp: total | 0.0000 | 0.0000 | 0.0000 | 21.1292 | 0.0000 | 19.0113 | 0.0000 |
| | Emp: gds prod | 0.0000 | 0.0000 | 0.0000 | -5.6002 | 0.0000 | -3.4010 | 0.0000 |
| | Emp: mining | 0.0000 | 0.0000 | 0.0000 | -0.0070 | 0.0000 | 0.0387 | 0.0000 |
| | Emp: const | 0.0000 | 0.0000 | 0.0000 | 0.5760 | 0.0000 | -0.0293 | 0.0000 |
| | Emp: mfg | 0.0000 | 0.0000 | 0.0000 | -12.0386 | 0.0000 | -11.7091 | 0.0000 |
| | Emp: dble gds | 0.0000 | 0.0000 | 0.0000 | 8.2241 | 0.0000 | 7.3166 | 0.0000 |
| | Emp: nondbles | 0.0000 | 0.0000 | 0.0000 | 4.8425 | 0.0000 | 4.4210 | 0.0000 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Emp: services | 0.0000 | 0.0000 | 0.0000 | -20.5499 | 0.0000 | -18.3414 | 0.0000 |
| | Emp: TTU | 0.0000 | 0.0000 | 0.0000 | 0.5845 | 0.0000 | 1.3539 | 0.0000 |
| | Emp: wholesale | 0.0000 | 0.0000 | 0.0000 | -0.3403 | 0.0000 | -0.7389 | 0.0000 |
| | Emp: retail | 0.0000 | 0.0000 | 0.0000 | -0.5199 | 0.0000 | -0.8898 | 0.0000 |
| | Emp: FIRE | 0.0000 | 0.0000 | 0.0000 | -0.2188 | 0.0000 | -0.1222 | 0.0000 |
| | Emp: Govt | 0.0000 | 0.0000 | 0.0000 | 4.1380 | 0.0000 | 3.6297 | 0.0000 |
| | Agg wkly hours | 0.0000 | 0.0000 | 0.0000 | -0.0254 | 0.0000 | -0.1423 | 0.0000 |
| | Avg hrs | 0.0000 | 0.0000 | 0.0000 | -0.0017 | 0.0000 | -0.0034 | 0.0000 |
| | Overtime: mfg | 0.0000 | 0.0000 | 0.0000 | -0.0012 | 0.0000 | 0.0056 | 0.0000 |
| | Avg hrs: mfg | 0.0000 | 0.0000 | 0.0000 | 0.0021 | 0.0000 | 0.0032 | 0.0000 |
| | NAPM empl | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0002 | 0.0000 |
| | AHE: goods | 0.0000 | 0.0000 | 0.0000 | -0.0375 | 0.0000 | -0.0903 | 0.0000 |
| | AHE: const | 0.0000 | 0.0000 | 0.0000 | -0.0101 | 0.0000 | 0.0019 | 0.0000 |
| | AHE: mfg | 0.0000 | 0.0000 | 0.0000 | 0.1489 | 0.0000 | 0.1924 | 0.0000 |
| **Housing** | Starts: nonfarm | -0.3610 | -0.0645 | -0.1796 | -0.3560 | -0.3507 | -0.2249 | -0.2836 |
| | Starts: NE | 0.0273 | 0.0026 | 0.0138 | 0.0249 | 0.0290 | 0.0149 | 0.0212 |
| | Starts: MW | 0.0678 | 0.0162 | 0.0334 | 0.0625 | 0.0662 | 0.0370 | 0.0528 |
| | Starts: South | 0.1879 | 0.0389 | 0.1052 | 0.1943 | 0.1907 | 0.1323 | 0.1563 |
| | Starts: West | 0.0983 | 0.0200 | 0.0371 | 0.0914 | 0.0863 | 0.0577 | 0.0725 |
| | BP: total | 0.0563 | 0.1004 | 0.0623 | -0.0248 | 0.2512 | 0.3437 | 0.1602 |
| | BP: NE | -0.0168 | -0.0168 | -0.0161 | -0.0019 | -0.0364 | -0.0516 | -0.0280 |
| | BP: MW | 0.0041 | -0.0137 | 0.0016 | 0.0075 | -0.0293 | -0.0534 | -0.0163 |
| | BP: South | -0.0697 | -0.0626 | -0.0487 | -0.0167 | -0.1489 | -0.1835 | -0.1060 |
| | BP: West | -0.0191 | -0.0271 | -0.0192 | -0.0033 | -0.0717 | -0.0847 | -0.0457 |
| **Consumption, Orders, and Inventories** | PMI | -0.0004 | 0.0000 | -0.0018 | -0.0009 | -0.0001 | -0.0008 | -0.0008 |
| | NAPM new ordrs | 0.0000 | 0.0000 | 0.0004 | -0.0001 | 0.0000 | 0.0001 | 0.0001 |
| | NAPM vendor del | 0.0004 | 0.0000 | 0.0012 | 0.0009 | 0.0001 | 0.0006 | 0.0006 |
| | NAPM Invent | -0.0001 | 0.0000 | 0.0002 | -0.0002 | 0.0000 | 0.0001 | 0.0000 |
| | Orders: cons gds | 0.0798 | 0.0038 | 0.0857 | 0.1453 | 0.0014 | 0.0889 | 0.0777 |
| | Orders: dble gds | -0.0483 | -0.0028 | -0.0781 | -0.0793 | -0.0019 | -0.0618 | -0.0541 |
| | Orders: cap gds | 0.0166 | 0.0009 | 0.0308 | 0.0318 | 0.0012 | 0.0245 | 0.0200 |
| | Unf orders: dble | -0.0784 | -0.0028 | -0.1620 | -0.1858 | -0.0143 | -0.1611 | -0.1051 |
| | M&T invent | 0.6258 | 0.0524 | 0.8131 | 1.6578 | -0.0779 | -0.2452 | 0.5246 |
| | M&T invent/sales | -0.3832 | -0.0391 | -0.5845 | -1.0292 | 0.0707 | 0.1671 | -0.3214 |
| | Real Consumption | 0.1907 | 0.0014 | -0.0440 | 0.4903 | 0.0117 | 0.0453 | 0.1319 |
| | M&T sales | -0.5867 | -0.0539 | -0.8204 | -1.5215 | 0.0983 | 0.1543 | -0.4853 |
| | Retail sales | -0.0732 | -0.0027 | 0.0172 | -0.1599 | -0.0054 | -0.0715 | -0.0646 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Consumer expect | 0.0001 | 0.0000 | 0.0001 | 0.0002 | 0.0000 | 0.0000 | 0.0001 |
| **Money and Credit** | M1 | 0.0077 | -0.0004 | -0.0029 | -0.0336 | -0.0268 | 0.0150 | -0.0073 |
| | M2 | -0.4236 | -0.2225 | -0.3305 | -0.4503 | -0.0974 | -0.3347 | -0.2755 |
| | Currency | 0.3266 | 0.1565 | 0.2542 | 0.3537 | 0.0146 | 0.4679 | 0.2580 |
| | M2 (real) | 0.5129 | 0.4194 | 0.6741 | 0.6209 | 0.3055 | 0.4118 | 0.4442 |
| | MB | 0.0108 | 0.0058 | 0.0129 | -0.0166 | 0.0229 | 0.0143 | 0.0077 |
| | Reserves tot | 0.0044 | -0.0004 | -0.0026 | 0.0119 | -0.0055 | -0.0025 | 0.0007 |
| | C&I loan plus | 0.0582 | 0.0837 | 0.1232 | 0.0127 | 0.0663 | 0.1512 | 0.0675 |
| | DC&I loans | -0.0001 | -0.0001 | -0.0002 | -0.0001 | -0.0001 | -0.0001 | -0.0001 |
| | Cons credit | 0.3297 | 0.2855 | 0.1911 | 0.3167 | 0.2131 | 0.3213 | 0.2682 |
| | Inst cred/PI | -0.0007 | 0.0008 | -0.0014 | -0.0029 | 0.0004 | -0.0048 | -0.0012 |
| **Bond** | Fed Funds | -0.0012 | 0.0193 | 0.0201 | -0.0039 | -0.0055 | -0.0012 | 0.0039 |
| | Comm paper | -0.0111 | -0.0059 | -0.0118 | -0.0047 | -0.0053 | -0.0037 | -0.0073 |
| | 3 mo T-bill | -0.0081 | 0.0021 | -0.0004 | -0.0248 | 0.0279 | -0.0151 | -0.0039 |
| | 6 mo T-bill | 0.0899 | 0.0149 | 0.0121 | 0.1329 | -0.0443 | 0.0252 | 0.0426 |
| | 1 yr T-bond | -0.1189 | -0.0447 | -0.0320 | -0.1319 | -0.0005 | -0.0201 | -0.0618 |
| | 5 yr T-bond | 0.0245 | 0.0486 | 0.0198 | 0.0103 | 0.0120 | -0.0192 | 0.0176 |
| | 10 yr T-bond | 0.0007 | -0.0444 | -0.0264 | 0.0154 | -0.0087 | 0.0195 | -0.0087 |
| | Aaa bond | -0.0123 | 0.0011 | 0.0216 | -0.0083 | -0.0008 | 0.0047 | 0.0018 |
| | Baa bond | 0.0147 | 0.0145 | -0.0017 | 0.0066 | 0.0003 | -0.0017 | 0.0050 |
| | CP-FF spread | 0.0275 | 0.0214 | 0.0233 | 0.0117 | 0.0068 | 0.0181 | 0.0183 |
| | 3 mo-FF spread | -0.0157 | -0.0036 | -0.0208 | 0.0089 | -0.0527 | -0.0079 | -0.0155 |
| | 6 mo-FF spread | 0.0825 | 0.0682 | 0.1015 | 0.0105 | 0.1392 | 0.0649 | 0.0779 |
| | 1 yr-FF spread | -0.0512 | -0.0358 | -0.0706 | -0.0133 | -0.0859 | -0.0623 | -0.0534 |
| | 5 yr-FF spread | 0.0276 | -0.0242 | 0.0039 | 0.0463 | 0.0222 | 0.0350 | 0.0209 |
| | 10 yr-FF spread | -0.0606 | 0.0058 | 0.0054 | -0.0936 | -0.0187 | -0.0399 | -0.0370 |
| | Aaa-FF spread | 0.0443 | 0.0072 | -0.0133 | 0.0646 | -0.0006 | 0.0201 | 0.0219 |
| | Baa-FF spread | -0.0040 | 0.0073 | 0.0103 | -0.0109 | 0.0074 | -0.0024 | 0.0011 |
| **Stock Market** | S&P 500 | -0.6113 | -0.1499 | -0.3178 | -0.7115 | -1.0012 | -0.5559 | -0.5395 |
| | S&P: indust | 0.3517 | 0.1267 | 0.2325 | 0.3768 | 0.6735 | 0.3306 | 0.3519 |
| | S&P div yield | -0.0597 | 0.0041 | -0.0229 | -0.0932 | -0.1004 | -0.0579 | -0.0476 |
| | S&P PE ratio | 0.0120 | 0.0033 | -0.0017 | 0.0132 | 0.0303 | 0.0107 | 0.0072 |

**(b) Slope**

| | | AUDUSD | EURUSD | GBPUSD | NZDUSD | USDCAD | USDJPY | GLOBAL |
|---|---|---|---|---|---|---|---|---|
| **Output and Income** | PI | 0.0000 | 0.1826 | 0.1980 | 0.0079 | 0.3414 | 0.2897 | 0.0000 |
| | PI less transfers | 0.0000 | -0.1422 | -0.1398 | -0.0015 | -0.3103 | -0.2413 | 0.0000 |
| | IP: total | 0.0000 | -0.1584 | 3.0288 | 0.0266 | 1.6489 | -3.3336 | 0.0000 |
| | IP: products | 0.0000 | 0.3677 | -1.7933 | 0.0359 | -0.3516 | 1.7471 | 0.0000 |
| | IP: final prod | 0.0000 | -1.6577 | -1.3778 | -0.1094 | -0.4312 | -0.8618 | 0.0000 |
| | IP: cons gds | 0.0000 | 1.0885 | -0.3462 | -0.1086 | 0.2862 | -0.1041 | 0.0000 |
| | IP: cons dble | 0.0000 | 0.0146 | 0.3124 | 0.0442 | 0.0320 | 0.2179 | 0.0000 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | IP: cons nondble | 0.0000 | 0.2431 | 1.4590 | 0.1637 | 0.1861 | 0.9785 | 0.0000 |
| | IP: bus eqpt | 0.0000 | 0.4428 | 0.4641 | 0.0386 | 0.2740 | 0.2992 | 0.0000 |
| | IP: matls | 0.0000 | 0.0620 | -1.5004 | -0.0258 | -0.7689 | 1.7370 | 0.0000 |
| | IP: dble matls | 0.0000 | 0.2062 | 0.3939 | 0.0517 | 0.4679 | 0.3571 | 0.0000 |
| | IP: nondble matls | 0.0000 | 0.0460 | 0.1369 | 0.0335 | 0.2432 | 0.0453 | 0.0000 |
| | IP: mfg | 0.0000 | -1.5152 | -2.9259 | -0.2678 | -3.2354 | -2.6568 | 0.0000 |
| | IP: res util | 0.0000 | -0.0342 | -0.0450 | -0.0047 | -0.0468 | -0.0436 | 0.0000 |
| | IP: fuels | 0.0000 | 0.0337 | 0.0618 | 0.0021 | 0.0150 | 0.0362 | 0.0000 |
| | NAPM prodn | 0.0000 | -0.0001 | -0.0003 | 0.0000 | -0.0002 | -0.0002 | 0.0000 |
| | Cap util | 0.0000 | 0.0129 | 0.0309 | 0.0016 | 0.0228 | 0.0225 | 0.0000 |
| **Labor Market** | Help wanted indx | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0001 | 0.0000 |
| | Help wanted/unemp | 0.0000 | 0.0000 | 0.0000 | -0.0056 | 0.0000 | -0.0039 | 0.0000 |
| | Emp CPS total | 0.0000 | 0.0000 | 0.0000 | 0.2274 | 0.0000 | 0.1155 | 0.0000 |
| | Emp CPS nonag | 0.0000 | 0.0000 | 0.0000 | -0.2691 | 0.0000 | -0.1686 | 0.0000 |
| | U: all | 0.0000 | 0.0000 | 0.0000 | -0.0015 | 0.0000 | -0.0003 | 0.0000 |
| | U: mean duration | 0.0000 | 0.0000 | 0.0000 | 0.0006 | 0.0000 | 0.0006 | 0.0000 |
| | U < 5 wks | 0.0000 | 0.0000 | 0.0000 | 0.0023 | 0.0000 | 0.0008 | 0.0000 |
| | U 5-14 wks | 0.0000 | 0.0000 | 0.0000 | 0.0031 | 0.0000 | 0.0067 | 0.0000 |
| | U 15+ wks | 0.0000 | 0.0000 | 0.0000 | -0.0452 | 0.0000 | -0.0445 | 0.0000 |
| | U 15-26 wks | 0.0000 | 0.0000 | 0.0000 | 0.0160 | 0.0000 | 0.0142 | 0.0000 |
| | U 27+ wks | 0.0000 | 0.0000 | 0.0000 | 0.0175 | 0.0000 | 0.0194 | 0.0000 |
| | UI claims | 0.0000 | 0.0000 | 0.0000 | 0.0083 | 0.0000 | 0.0113 | 0.0000 |
| | Emp: total | 0.0000 | 0.0000 | 0.0000 | 21.1292 | 0.0000 | 19.0113 | 0.0000 |
| | Emp: gds prod | 0.0000 | 0.0000 | 0.0000 | -5.6002 | 0.0000 | -3.4010 | 0.0000 |
| | Emp: mining | 0.0000 | 0.0000 | 0.0000 | -0.0070 | 0.0000 | 0.0387 | 0.0000 |
| | Emp: const | 0.0000 | 0.0000 | 0.0000 | 0.5760 | 0.0000 | -0.0293 | 0.0000 |
| | Emp: mfg | 0.0000 | 0.0000 | 0.0000 | -12.0386 | 0.0000 | -11.7091 | 0.0000 |
| | Emp: dble gds | 0.0000 | 0.0000 | 0.0000 | 8.2241 | 0.0000 | 7.3166 | 0.0000 |
| | Emp: nondbles | 0.0000 | 0.0000 | 0.0000 | 4.8425 | 0.0000 | 4.4210 | 0.0000 |
| | Emp: services | 0.0000 | 0.0000 | 0.0000 | -20.5499 | 0.0000 | -18.3414 | 0.0000 |
| | Emp: TTU | 0.0000 | 0.0000 | 0.0000 | 0.5845 | 0.0000 | 1.3539 | 0.0000 |
| | Emp: wholesale | 0.0000 | 0.0000 | 0.0000 | -0.3403 | 0.0000 | -0.7389 | 0.0000 |
| | Emp: retail | 0.0000 | 0.0000 | 0.0000 | -0.5199 | 0.0000 | -0.8898 | 0.0000 |
| | Emp: FIRE | 0.0000 | 0.0000 | 0.0000 | -0.2188 | 0.0000 | -0.1222 | 0.0000 |
| | Emp: Govt | 0.0000 | 0.0000 | 0.0000 | 4.1380 | 0.0000 | 3.6297 | 0.0000 |
| | Agg wkly hours | 0.0000 | 0.0000 | 0.0000 | -0.0254 | 0.0000 | -0.1423 | 0.0000 |
| | Avg hrs | 0.0000 | 0.0000 | 0.0000 | -0.0017 | 0.0000 | -0.0034 | 0.0000 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Overtime: mfg | 0.0000 | 0.0000 | 0.0000 | -0.0012 | 0.0000 | 0.0056 | 0.0000 |
| | Avg hrs: mfg | 0.0000 | 0.0000 | 0.0000 | 0.0021 | 0.0000 | 0.0032 | 0.0000 |
| | NAPM empl | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0002 | 0.0000 |
| | AHE: goods | 0.0000 | 0.0000 | 0.0000 | -0.0375 | 0.0000 | -0.0903 | 0.0000 |
| | AHE: const | 0.0000 | 0.0000 | 0.0000 | -0.0101 | 0.0000 | 0.0019 | 0.0000 |
| | AHE: mfg | 0.0000 | 0.0000 | 0.0000 | 0.1489 | 0.0000 | 0.1924 | 0.0000 |
| **Housing** | Starts: nonfarm | -0.3610 | -0.0645 | -0.1796 | -0.3560 | -0.3507 | -0.2249 | 0.0000 |
| | Starts: NE | 0.0273 | 0.0026 | 0.0138 | 0.0249 | 0.0290 | 0.0149 | 0.0000 |
| | Starts: MW | 0.0678 | 0.0162 | 0.0334 | 0.0625 | 0.0662 | 0.0370 | 0.0000 |
| | Starts: South | 0.1879 | 0.0389 | 0.1052 | 0.1943 | 0.1907 | 0.1323 | 0.0000 |
| | Starts: West | 0.0983 | 0.0200 | 0.0371 | 0.0914 | 0.0863 | 0.0577 | 0.0000 |
| | BP: total | 0.0563 | 0.1004 | 0.0623 | -0.0248 | 0.2512 | 0.3437 | 0.0000 |
| | BP: NE | -0.0168 | -0.0168 | -0.0161 | -0.0019 | -0.0364 | -0.0516 | 0.0000 |
| | BP: MW | 0.0041 | -0.0137 | 0.0016 | 0.0075 | -0.0293 | -0.0534 | 0.0000 |
| | BP: South | -0.0697 | -0.0626 | -0.0487 | -0.0167 | -0.1489 | -0.1835 | 0.0000 |
| | BP: West | -0.0191 | -0.0271 | -0.0192 | -0.0033 | -0.0717 | -0.0847 | 0.0000 |
| **Consumption, Orders, and Inventories** | PMI | -0.0004 | 0.0000 | -0.0018 | -0.0009 | -0.0001 | -0.0008 | 0.0033 |
| | NAPM new ordrs | 0.0000 | 0.0000 | 0.0004 | -0.0001 | 0.0000 | 0.0001 | -0.0012 |
| | NAPM vendor del | 0.0004 | 0.0000 | 0.0012 | 0.0009 | 0.0001 | 0.0006 | -0.0011 |
| | NAPM Invent | -0.0001 | 0.0000 | 0.0002 | -0.0002 | 0.0000 | 0.0001 | -0.0006 |
| | Orders: cons gds | 0.0798 | 0.0038 | 0.0857 | 0.1453 | 0.0014 | 0.0889 | -0.1665 |
| | Orders: dble gds | -0.0483 | -0.0028 | -0.0781 | -0.0793 | -0.0019 | -0.0618 | 0.1551 |
| | Orders: cap gds | 0.0166 | 0.0009 | 0.0308 | 0.0318 | 0.0012 | 0.0245 | -0.0457 |
| | Unf orders: dble | -0.0784 | -0.0028 | -0.1620 | -0.1858 | -0.0143 | -0.1611 | -0.1003 |
| | M&T invent | 0.6258 | 0.0524 | 0.8131 | 1.6578 | -0.0779 | -0.2452 | -1.7097 |
| | M&T invent/sales | -0.3832 | -0.0391 | -0.5845 | -1.0292 | 0.0707 | 0.1671 | 0.8668 |
| | Real Consumption | 0.1907 | 0.0014 | -0.0440 | 0.4903 | 0.0117 | 0.0453 | -0.2704 |
| | M&T sales | -0.5867 | -0.0539 | -0.8204 | -1.5215 | 0.0983 | 0.1543 | 1.4066 |
| | Retail sales | -0.0732 | -0.0027 | 0.0172 | -0.1599 | -0.0054 | -0.0715 | 0.0953 |
| | Consumer expect | 0.0001 | 0.0000 | 0.0001 | 0.0002 | 0.0000 | 0.0000 | 0.0001 |
| **Money and Credit** | M1 | 0.0077 | -0.0004 | -0.0029 | -0.0336 | -0.0268 | 0.0150 | 0.0532 |
| | M2 | -0.4236 | -0.2225 | -0.3305 | -0.4503 | -0.0974 | -0.3347 | 0.2513 |
| | Currency | 0.3266 | 0.1565 | 0.2542 | 0.3537 | 0.0146 | 0.4679 | -0.2473 |
| | M2 (real) | 0.5129 | 0.4194 | 0.6741 | 0.6209 | 0.3055 | 0.4118 | -0.3709 |
| | MB | 0.0108 | 0.0058 | 0.0129 | -0.0166 | 0.0229 | 0.0143 | -0.0053 |
| | Reserves tot | 0.0044 | -0.0004 | -0.0026 | 0.0119 | -0.0055 | -0.0025 | -0.0146 |
| | C&I loan plus | 0.0582 | 0.0837 | 0.1232 | 0.0127 | 0.0663 | 0.1512 | 0.0437 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | DC&I loans | -0.0001 | -0.0001 | -0.0002 | -0.0001 | -0.0001 | -0.0001 | 0.0000 |
| | Cons credit | 0.3297 | 0.2855 | 0.1911 | 0.3167 | 0.2131 | 0.3213 | -0.0729 |
| | Inst cred/PI | -0.0007 | 0.0008 | -0.0014 | -0.0029 | 0.0004 | -0.0048 | -0.0026 |
| **Bond** | Fed Funds | -0.0012 | 0.0193 | 0.0201 | -0.0039 | -0.0055 | -0.0012 | 0.0223 |
| | Comm paper | -0.0111 | -0.0059 | -0.0118 | -0.0047 | -0.0053 | -0.0037 | -0.0008 |
| | 3 mo T-bill | -0.0081 | 0.0021 | -0.0004 | -0.0248 | 0.0279 | -0.0151 | 0.0155 |
| | 6 mo T-bill | 0.0899 | 0.0149 | 0.0121 | 0.1329 | -0.0443 | 0.0252 | -0.0952 |
| | 1 yr T-bond | -0.1189 | -0.0447 | -0.0320 | -0.1319 | -0.0005 | -0.0201 | 0.0904 |
| | 5 yr T-bond | 0.0245 | 0.0486 | 0.0198 | 0.0103 | 0.0120 | -0.0192 | 0.0016 |
| | 10 yr T-bond | 0.0007 | -0.0444 | -0.0264 | 0.0154 | -0.0087 | 0.0195 | -0.0054 |
| | Aaa bond | -0.0123 | 0.0011 | 0.0216 | -0.0083 | -0.0008 | 0.0047 | -0.0127 |
| | Baa bond | 0.0147 | 0.0145 | -0.0017 | 0.0066 | 0.0003 | -0.0017 | 0.0023 |
| | CP-FF spread | 0.0275 | 0.0214 | 0.0233 | 0.0117 | 0.0068 | 0.0181 | -0.0074 |
| | 3 mo-FF spread | -0.0157 | -0.0036 | -0.0208 | 0.0089 | -0.0527 | -0.0079 | 0.0068 |
| | 6 mo-FF spread | 0.0825 | 0.0682 | 0.1015 | 0.0105 | 0.1392 | 0.0649 | 0.0342 |
| | 1 yr-FF spread | -0.0512 | -0.0358 | -0.0706 | -0.0133 | -0.0859 | -0.0623 | -0.0437 |
| | 5 yr-FF spread | 0.0276 | -0.0242 | 0.0039 | 0.0463 | 0.0222 | 0.0350 | 0.0004 |
| | 10 yr-FF spread | -0.0606 | 0.0058 | 0.0054 | -0.0936 | -0.0187 | -0.0399 | 0.0055 |
| | Aaa-FF spread | 0.0443 | 0.0072 | -0.0133 | 0.0646 | -0.0006 | 0.0201 | -0.0040 |
| | Baa-FF spread | -0.0040 | 0.0073 | 0.0103 | -0.0109 | 0.0074 | -0.0024 | 0.0008 |
| **Stock Market** | S&P 500 | -0.6113 | -0.1499 | -0.3178 | -0.7115 | -1.0012 | -0.5559 | -0.3789 |
| | S&P: indust | 0.3517 | 0.1267 | 0.2325 | 0.3768 | 0.6735 | 0.3306 | 0.3601 |
| | S&P div yield | -0.0597 | 0.0041 | -0.0229 | -0.0932 | -0.1004 | -0.0579 | -0.0920 |
| | S&P PE ratio | 0.0120 | 0.0033 | -0.0017 | 0.0132 | 0.0303 | 0.0107 | -0.0543 |

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# APPENDIX

## 2A. MFIV Introduction[31]

This section briefly introduces why MFIV can measure variance. Consider an integrated variance contract with maturity $T$, where $F_t$ is continuous, following standard Brownian motion $B_t^*$, and the instantaneous variance $v_t$ can have jumps. Define its payoff as $IV_T$, and its time-zero value under risk-neutral expectation $E_0^*[IV_T]$ is what I aim to measure.

$$\frac{dF_t}{F_t} = \sqrt{v_t} dB_t^*$$

$$IV_T := \int_0^T (\frac{dF_t}{F_t})^2 = \int_0^T v_t \, dt$$

To replicate the value of the variance contract, Dupire (1993) and Neuberger (1994) came up with the portfolio of OTM options $OP_T$ and define the measure $MFIV$ as its time-zero value $E_0^*[OP_T]$, which is proved to be equivalent with $E_0^*[IV_T]$ (Bondarenko, 2014).

$$OP_T := 2(\int_0^{F_0} \frac{P_T(K)}{K^2} dK + \int_{F_0}^{\infty} \frac{C_T(K)}{K^2} dK) = 2\int_0^{\infty} \frac{M_T(K)}{K^2} dK$$

$$MFIV := E_0^*[OP_T] = 2\int_0^{\infty} \frac{M_0(K)}{K^2} dK$$

$$E_0^*[IV_T] = MFIV$$

Bondarenko (2014) introduced a realized variance contract $RV_T$, relaxing the assumption of continuous process of $F_t$ to allow for discrete sampling up to a daily frequency. Its value is proved able to be replicated by the portfolio constructed above as well (Bondarenko, 2014).

$$RV_T := 2\sum_{i=1}^{n} (\frac{F_i - F_{i-1}}{F_{i-1}} - ln(\frac{F_i}{F_{i-1}}))$$

$$E_0^*[RV_T] = MFIV$$

## 2B. FX options interpolation

(1) Come up with a set of strikes within a reasonable range $(0.75 \min_t(S_t), 1.25 \max_t(S_t))$, with an interval of 0.001 except for USDJPY with interval 0.05. Denote them as $K_1, K_2, \dots, K_n, \dots, K_N$.
(2) For each $K$, calculate its implied volatility $\sigma(K)$ using the Vanna-Volga method proposed by Castagana and Mercurio (2007) and Castagana (2010):

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[31] This section mainly refers to Bondarenko (2014).

$$\sigma(K) = \sigma_{atm} + \frac{-\sigma_{atm} + \sqrt{\sigma_{atm}^2 + d_1(K)d_2(K)(2\sigma_{atm}D_1(K) + D_2(K))}}{d_1(K)d_2(K)}$$

where

$$D_1(K) = \frac{\ln\left[\frac{K_{atm}}{K}\right]\ln\left[\frac{K_{25\delta c}}{K}\right]}{\ln\left[\frac{K_{atm}}{K_{25\delta p}}\right]\ln\left[\frac{K_{25\delta c}}{K_{25\delta p}}\right]}\sigma_{25\delta p} + \frac{\ln\left[\frac{K}{K_{25\delta p}}\right]\ln\left[\frac{K_{25\delta c}}{K}\right]}{\ln\left[\frac{K_{atm}}{K_{25\delta p}}\right]\ln\left[\frac{K_{25\delta c}}{K_{atm}}\right]}\sigma_{atm} + \frac{ln[\frac{K}{K_{25\delta p}}]ln[\frac{K}{K_{atm}}]}{ln[\frac{K_{25\delta c}}{K_{25\delta p}}]ln[\frac{K_{25\delta c}}{K_{atm}}]}\sigma_{25\delta c} - \sigma_{atm}$$

$$D_2(K) = \frac{\ln\left[\frac{K_{atm}}{K}\right]\ln\left[\frac{K_{25\delta c}}{K}\right]}{\ln\left[\frac{K_{atm}}{K_{25\delta p}}\right]\ln\left[\frac{K_{25\delta c}}{K_{25\delta p}}\right]}d_1(K_{25\delta p})d_2(K_{25\delta p})(\sigma_{25\delta p} - \sigma_{atm})^2 + \frac{ln[\frac{K}{K_{25\delta p}}]ln[\frac{K}{K_{atm}}]}{ln[\frac{K_{25\delta c}}{K_{25\delta p}}]ln[\frac{K_{25\delta c}}{K_{atm}}]}d_1(K_{25\delta c})d_2(K_{25\delta c})(\sigma_{25\delta c} - \sigma_{atm})^2$$

$$d_1(K_{25\delta p}) = \frac{\log\left[\frac{S_t}{K_{25\delta p}}\right] + \left(r^d - r^f + 0.5\sigma_{25\delta p}^2\right)T}{\sigma_{25\delta p}\sqrt{T}}, d_2(K_{25\delta p}) = d_1(K_{25\delta p}) - \sigma_{25\delta p}\sqrt{T},$$

$$d_1(K_{25\delta c}) = \frac{\log\left[\frac{S_t}{K_{25\delta c}}\right] + \left(r^d - r^f + 0.5\sigma_{25\delta c}^2\right)T}{\sigma_{25\delta c}\sqrt{T}}, d_2(K_{25\delta c}) = d_1(K_{25\delta c}) - \sigma_{25\delta c}\sqrt{T},$$

$$d_1(K) = \frac{log[\frac{S_t}{K}] + (r^d - r^f + 0.5\sigma^2)T}{\sigma\sqrt{T}}, d_2(K) = d_1(K) - \sigma\sqrt{T}, \sigma \approx \sigma_{atm}$$

**2C. Realized Volatility**

I follow the concept of a squared weighted return $r_w^2$ proposed by Andersen et al. (2015) who showed that it is the notion of return variation priced by the MFIV formula.

$$r_{t,w}^2 = 2(r_{t,a} - r_{t,l})$$

$$r_{t,l} = ln(S_t) - ln(S_{t-1}),\ r_{t,a} = (S_t - S_{t-1})/S_{t-1}$$

$$S_t: exchange\ rate\ spot\ rate\ at\ time\ t.$$

$$RV_{w,t,t+T} := \sum_{t\prime=t+1}^{t\prime=t+T} r_{t\prime,w}^2 = \frac{2}{3}RV_{l,t,t+T} + \frac{1}{3}RV_{a,t,t+T}$$

$$RV_{l,t,t+T} := \sum_{t\prime=t+1}^{t\prime=t+T} r_{t\prime,l}^2, \quad RV_{a,t,t+T} := \sum_{t\prime=t+1}^{t\prime=t+T} r_{t\prime,a}^2$$

# VITA

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