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Exchange Rate Risk Compensation in International ETFs

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Abstract

We study exchange rate risk compensation in international ETFs from the perspective of a U.S. investor by using the Dollar and Carry currency risk factors. We find that U.S. investors are compensated for taking currency risk. In particular, when we estimate risk factor loadings conditionally, using 60-month rolling windows, in the sample period between January 1997 and June 2015, taking an additional unit of Dollar risk is associated with 0.94 percentage points more excess return per annum, while an additional unit of Carry risk is associated with an increase in excess return of 4.74 percentage points per annum.

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1. Introduction

ETF investments are growing worldwide, and have been since their spawn in 1990 (BlackRock, 2018). Many ETFs are investing internationally. We answer the following question in our thesis: Are international ETF investors compensated for bearing exchange rate risk?

Lustig, et al. (2011) identify two currency risk factors, the Dollar and Carry factors. Brusa, et al. (2014) find that the factors are priced in international equity indices, mutual funds and hedge funds. We extend the work of Lustig, et al. (2011) and Brusa, et al. (2014) by studying exchange rate risk in exchange-traded funds which invest internationally. Specifically, we study 26 ETFs which track national or regional indices, and which invest in assets denominated in a single currency at any given point in time. To our knowledge, no such study is performed on ETFs to date.

We use models with one equity risk factor and two currency risk factors to estimate exchange rate risk prices, and find that currency risk is priced in international ETFs in our sample when we estimate our models conditionally. Because of data availability on two of our risk factors, we examine two different sample periods: January 1997 to June 2015 and January 1997 to September 2017. We find that U.S. investors are compensated for taking carry trade risk regardless of sample period and rolling window size. In the case of 60-month rolling windows-estimation on our longer sample period, an additional unit of Carry risk is associated with 4.74¹ percentage points higher excess return on ETFs per annum, which is similar to the 0.418 percentage point increase in excess return per month in Brusa, et al. (2014). We find that one unit of Dollar risk is priced at 0.94 percentage points for the sample period ending in June 2015, while it is not priced for the sample period ending in September 2017. These results differ from the 0.293 percentage point increase in excess return per unit of Dollar risk that Brusa, et al. (2014) find, which might be explained by the differences of the studies. The cross-sections of test assets and currencies are larger in Brusa, et al. (2014), their equity risk factor

¹ The risk prices we report in the abstract and introduction are estimated in models using the local world market excess return (LWMKT) as the equity risk factor. We explain how we construct the risk factor in section 3.8. All estimated risk prices are reported in table 4.1 and table 4.2.

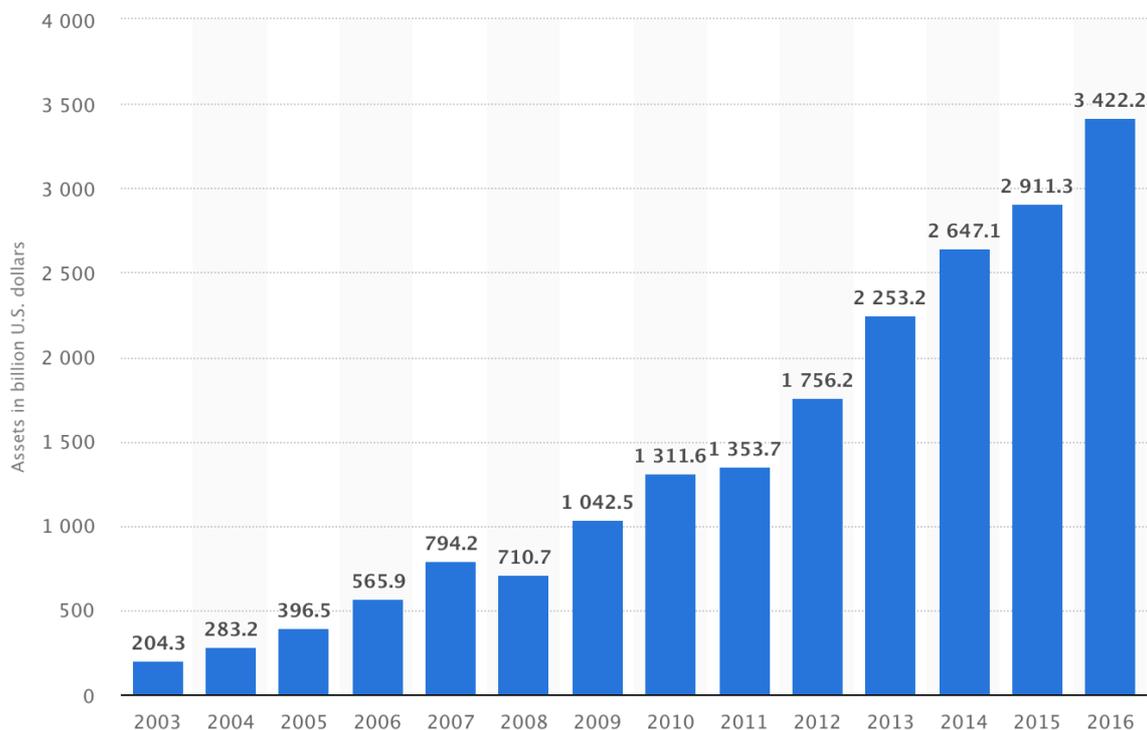
is constructed differently from ours, their sample period is longer, and their test assets are equity indices, while our test assets are exchange-traded funds.

An ETF is, as the name implies, a fund listed on a stock exchange, and is traded in the same manner as stocks. These funds make it possible to get exposure to stock and bond indices, commodities and exchange rates just as easy as trading with regular stocks. Most ETFs are “index trackers” (Oslo Stock Exchange, n.d.) or passively managed funds which attempt to provide the same return as a given benchmark index, and which offer investors low internal costs. ETFs are popular among investors, and assets under management have grown nearly exponentially the last decades, as shown in figure 1.

Figure 1

ETF Assets Under Management 2003-2016

The figure shows the development of assets under management of global ETFs. Figures are in billion U.S. Dollars (Statista, 2018).



We proceed as follows. Section 2 discusses literature relevant to our thesis. Section 3 presents how we construct our test assets and variables. Section 4 presents our methodology and some

theoretical background for our econometric framework. Section 5 presents our results, which we discuss in section 6. Section 7 concludes and suggests topics for further research.

2. Literature review

In this section, we discuss literature relevant to our thesis, in the fields of asset pricing, international asset pricing, currency risk factors and the uncovered interest rate parity puzzle, and the combination of equity and currency risk factors.

2.1 Asset Pricing and International Asset Pricing Literature

Asset pricing literature was revolutionized in the 1960s through the introduction of the Capital Asset Pricing Model (CAPM), by works such as Sharpe (1964) and Lintner (1965). Put simply, the CAPM identifies an asset's (or a group of assets') discount factor by multiplying a market excess return (market return minus a risk-free rate) with the asset's exposure to the market excess return, and adding an appropriate risk-free rate.

Several models exist for estimating quantities and prices of global asset risk. By using world market excess return as the CAPM market factor, the CAPM is easily extended to the World CAPM. In this model, consumption and investment opportunities are equal across countries. Addressing this issue, Adler and Dumas (1983) points to empirical deviations from Purchasing Power Parity (PPP), and introduce the International CAPM model (Adler and Dumas, 1983). The model, which was operationalized by Dumas and Solnik (1995), includes currency excess returns obtained from investing in Pound Sterling, Japanese Yen and Euro/Deutsche Mark as risk factors, in addition to the world market equity excess return.

CAPM has been the target of a lot of criticism. Among the most notable critiques are Fama and French (1993), who note that the CAPM shows little relation to average returns on common U.S. stocks. They introduce a three-factor model consisting of excess market return and the excess return of the Small-Minus-Big (SMB) and High-Minus-Low (HML) factors. The SMB factor is constructed by going long (short) in portfolios of stocks of smaller (bigger) market capitalization size firms, while the HML factor is constructed by going long (short) in portfolios of stocks of high (low) book-to-market equity value ratio. Carhart (1997) extends the work of Fama and French (1993) by adding a fourth factor, the Winners-Minus-Losers (WML) or Momentum factor. The WML factor is constructed by going long (short) in portfolios of stocks with higher (lower) return in previous time periods. The model is interchangeably referred to as the Fama French Four-Factor Model or the Carhart Four-Factor

model. Fama and French (2012) further extends the model to a global version of the four-factor model, by incorporating international stock portfolios to the risk factors. The model does not take into consideration exchange rate risk, and thus differs fundamentally from the World CAPM and International CAPM in its approach to global risk.

The Fama and French factor models have become a standard benchmark in financial literature. It is important to note however, that their criticism towards the CAPM was directed to the static version of the model. In the static CAPM, betas of the test assets remain constant over time. Jagannathan and Wang (1996) introduce the conditional CAPM, that allow for time-varying betas by assuming that the CAPM holds period by period. The conditional version empirically outperforms static estimations of the model.

2.2 Currency Risk Factor Literature and the UIP Puzzle

Growing amounts of financial literature is devoted to risk-based models for measuring international investors' compensation for exchange rate risk. Risk factors constructed by portfolios of currencies provide explanation for international risk compensation (Lustig, et al., 2011). In particular, Lustig, et al. (2011) employ two currency components, originally coined the dollar risk factor RX and the carry risk factor HML (High Minus Low), which are investment strategies in currency markets. From a US investor's perspective, the RX factor is the excess return obtained by loaning in US Dollars and investing in all other currencies in the market, while the HML factor is the excess return obtained by going long in portfolios of high interest rate currencies and going short in portfolios of low interest rate currencies (Lustig, et al., 2011).

According to the uncovered interest rate parity (UIP), the expected change in exchange rate between two countries should be equal to the interest rate differential between them. Thus, if UIP holds, the currency strategies of Lustig, et al. (2011) will not be risky and will yield no excess return. However, the failure of UIP, and the phenomenon of higher interest rate currencies' tendency to appreciate against lower interest rate currency, is widely recognized. Empirical works such as Fama (1984) and Hansen and Hodrick (1980) prove that the regression coefficient on interest rate differentials is not necessarily equal to 1. This is referred to as the UIP puzzle or the forward premium anomaly (Backus, Foresi and Telmer, 2001). Some recent literature attempts to offer explanations for this anomaly. Verdelhan (2010)

suggests a theoretical model in which he assigns the failure of UIP to a time-varying, counter-cyclical risk premium that is higher in domestically bad economic times. Christiansen and Rinaldo (2010) finds that parts of carry trade excess return is empirically explained by foreign exchange rate volatility, and establishes an empirical correlation between carry trade excess return and the stock market. Common to these papers, and many others, is that excess return obtained because of the failure of UIP is time-varying. Engel (2016) notes that for a risk-based explanation of the anomaly to exist, short-term deposits in higher interest currencies must be relatively riskier - because of the risk of exchange rate movements - and therefore, the risk premium must be time-varying and co-vary with the interest rate differential. This notion is in line with, and provides a, risk-based explanation for the carry trade HML factor of Lustig, et al. (2011). Another line of research offers a more characteristics-based explanation for currency risk premium, such as Rinaldo and Söderlind (2010), who suggest that some currencies are viewed as safe havens, and as such earns a lower risk premium.

To elaborate on the subject of risk-based explanations: The carry trade risk factor corresponds to the change in exchange rates between baskets of high and low interest rate currencies. It offers an intuitive risk-based interpretation: The higher the interest rate of an individual currency, the higher the exposure to carry trade risk (Verdelhan, 2017a). Thus, it is a slope factor where high interest rate currencies load higher than low interest rate currencies (Lustig, et al., 2011).

The dollar factor corresponds to the average change in the exchange rate between the U.S. dollar and all other currencies (Verdelhan, 2017a). The risk-based interpretation is not as intuitive for the dollar factor as for the carry factor, but Verdelhan (2017) proposes that it is the risk of Dollar appreciation for a U.S. investor.

2.3 Combining Equity and Currency Risk Factors

Recent academic literature combines the traditional asset pricing models with the risk-based explanation for the UIP puzzle, and use both equity and currency risk factors to explain international equity return. In particular, the International CAPM Redux model by Brusa, et al. (2014), combines an equity market excess return factor with the two currency risk factors of Lustig, et al. (2011) to price international equity indices.

Brusa et al (2014) compares the International CAPM Redux model to various international equity models, such as the International CAPM (Adler and Dumas, 1983), World CAPM of Sharpe (1964) and Lintner (1965), and the global Fama French Factor model (Fama and French, 2012). The three latter models include one common equity market factor; the world market equity excess return. Brusa, et al. (2014) suggest an alteration to the world market factor, so that the hypothetical return gained by investing in the world market is denominated in local currencies, before the individual return by investing in the world market denominated in each currency is weighted and averaged, and the risk-free rate, the US 30-day Treasury Bill return, is subtracted to obtain excess return. This equity factor is referred to as the local world market equity factor, LWMKT. The International CAPM Redux model outperforms the World CAPM and the International CAPM and delivers similar results to the global version of the Fama French model. Brusa, et al. (2014) note that time-variation in prices of risk appear key to this result.

3. Data

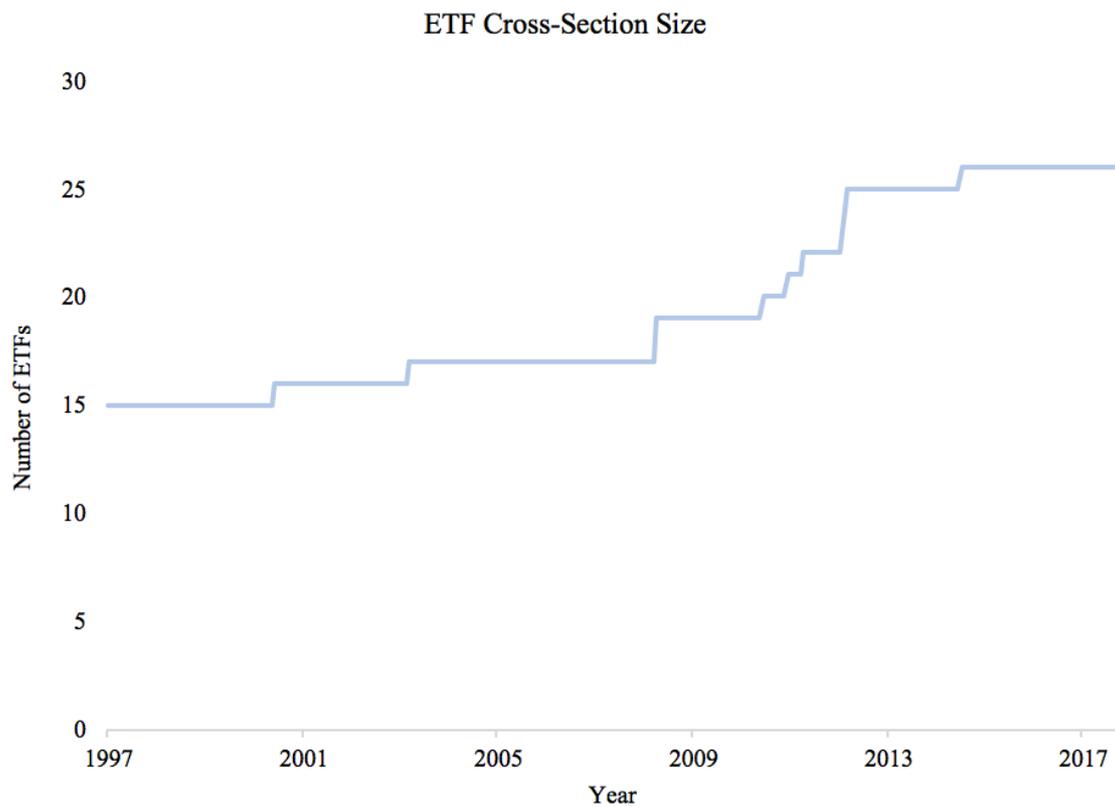
In this section, we describe the construction of our test assets and explanatory variables.

3.1 ETF Data

The ETF excess returns are our test assets. We obtain our ETF data using DataStream. We download daily adjusted prices from 26 exchange-traded funds issued by iShares. We only include ETFs that track indices in national or regional indices, such that no ETFs in our sample data invest in assets denominated in different currencies. We use ETFs issued by iShares because they are, and have been over time, a leading ETF provider. As of December 31, 2016, iShares had over 800 ETFs globally with more than 1.5 trillion U.S. dollars in assets under management (iShares, 2017). This offers the advantage of access to a wide range of asset markets and a longer horizon of data than what is the case for many of their competitors. Our ETFs enter the data set at different points in time, depending on data availability. As figure 2 shows, our sample data includes at the most (least) 26 (15) ETFs. All ETFs are listed on the New York Stock Exchange Archipelago Exchange (NYSE ARCA) database, except for The iShares MSCI Turkey Investable Market Index Fund, which is listed on the Nasdaq Stock Market (NASDAQ). We compute ETF excess returns by subtracting the U.S. 30-day Treasury Bill rate from the ETF returns. The time series of T-Bills is obtained from the data library on Kenneth French's website (French, 2017).

Figure 2
ETF Data

The figure reports the number of ETFs in our sample data at each point in time. Test assets are monthly returns of ETFs in excess of the corresponding 30-day Treasury Bill rate. ETFs enter the data set according to appendix A.



3.2 Currency Data

We obtain daily spot and one-month forward exchange rate series (midpoint quotes) using DataStream. The spot rates are collected using the Thomson Reuters database, whereas the forward rates are collected using Thomson Reuters Forward Rates (henceforth TR) and WM/Reuters Closing Forward Rates (henceforth WMR). We merge the forward rates from TR and WMR to obtain our main data set.

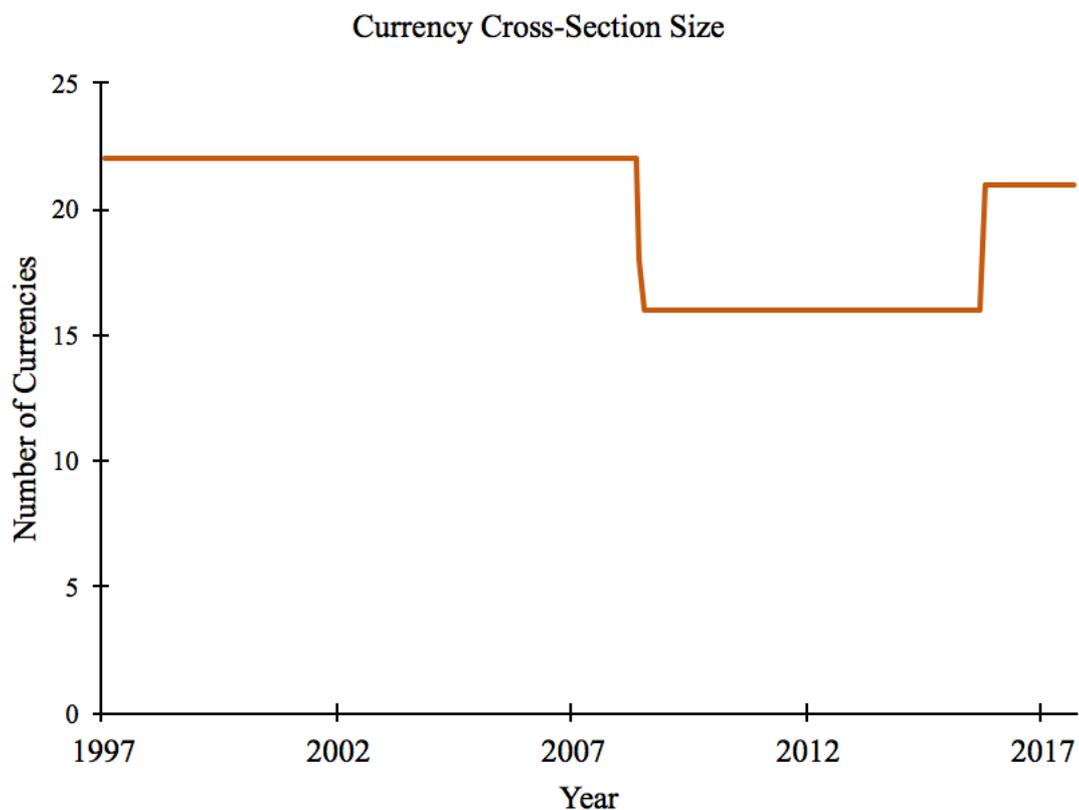
We build end-of-month series of the daily spot and forward rates spanning from January 1997 to September 2017. Countries enter our currency data set at different points in time depending on the availability of spot and forward exchange rates, as seen in appendix A. Our data set

spans a total of 28 currencies. As illustrated in figure 3, the cross-sections contain at the most 22 different currencies, and at the least 16, due to the introduction of the Euro in January 1999. Currencies of countries in the Euro area leave our set of data after December 1998.

The forward exchange rates of the Australian Dollar and the New Zealand Dollar, and the Pound Sterling spot rate, are originally denominated in units of U.S. Dollar per foreign currency. We use the inverse forward exchange rate for the two currencies, so that they express units of Australian Dollar per U.S. Dollar, and New Zealand Dollar per U.S. Dollar. Appendix A displays our data coverage of currencies.

Figure 3
Currency Data

The figure reports the number of currencies in the cross-section at each point in time. Currencies enter the data set according to their data coverage, see appendix A. The cross-section decreases in January 1999 as Euro area currencies are replaced by the Euro.



3.3 Currency Portfolios and the Carry Factor

We construct our currency portfolios in the manner of Lustig, et al. (2011) and Brusa, et al. (2014). For each month t , we build six portfolios of currencies sorted by their log forward discounts in period $(t-1)$. The excess return of each portfolio is reported in Appendix B. In normal conditions, forward rates satisfy the covered interest rate parity condition. Although covered interest parity empirically does not hold in the year of 2008 (Jones, 2009), we accept and utilize the methodology of previous literature. Thus, the log forward discount is equal to the interest rate differential:

$$f_t - s_t \approx i_t^* - i_t . \quad (1)$$

where i^* and i denote the foreign and domestic nominal risk-free rates. f and s denotes, respectively, the log forward exchange rate and the log spot exchange rate in units of foreign currency per U.S. Dollar. An increase in s means an appreciation of the U.S. dollar relative to the foreign currency.

The first portfolio contains the lowest interest rate currencies, while the last portfolio contains the highest. These portfolios are rebalanced at the end of each month, so that we sort portfolios on current interest rates rather than average interest rates, which yields a higher Sharpe-ratio for carry trade (Lustig, et al., 2011). At each time t , we go long in the last portfolio, and short in the first portfolio. The log excess return, rx , on buying a foreign currency in the forward market and selling it in the spot market after one month is computed as:

$$rx_t = f_{t-1} - s_t \quad (2)$$

The excess returns on the carry factor at each time t , Carry_t , are computed as the difference in returns on the last portfolio and the first portfolio; the returns on going long in the portfolio with the highest interest rates currencies and shorting the portfolio with the lowest interest rate currencies. The return on each portfolio is constructed as the average of the currencies' excess returns in the given portfolio. In table 1, we see that the average excess return earned by a U.S. investor on the carry trade strategy is 9.39%, where the investment period spans from January 1997 to September 2017. The Carry factor is the excess returns of investing in high- and borrowing in low-interest rate currencies:

$$Carry_t = \frac{1}{N_H} \sum_{i \in H} rx_t^i - \frac{1}{N_L} \sum_{i \in L} rx_t^i \quad (3)$$

3.4 Dollar Factor

The Dollar excess return is constructed in the following way: in each period of time, we assume that an U.S. investor borrows in the U.S. and invests in all other currencies in our data set. At each time t , the excess return generated from the investment strategy is computed in the following way, the log forward discount in the previous period of time minus the change in the spot rate:

$$rx_t = f_{t-1} - s_{t-1} - \Delta s_t \quad (4)$$

Excess return is computed in this manner individually for all currencies in our data set. At each time t , we average the currency excess returns to compute the Dollar factor:

$$Dollar_t = \frac{1}{N} \sum_i rx_t^i \quad (5)$$

where N denotes the number of currencies in our sample, and i denotes each currency.

3.5 VDollar Factor

As a robustness measure, we include the Dollar factor estimated by Adrien Verdelhan, downloaded from his website (Verdelhan, 2017b), henceforth VDollar. The factor is the excess return gained by loaning US Dollars and investing in all foreign currencies. VDollar is constructed with a broader selection of currencies than the Dollar factor. The sample period ranges from January 1997 to June 2015.

3.6 VCarry Factor

We download the carry trade risk factor from Adrien Verdelhan's website (Verdelhan, 2017b), henceforth VCarry in our thesis. Like our Carry factor, it is a currency excess return factor, constructed by going short (long) in low (high) interest rate currencies. The currency sample size, the cross-section of currencies at each point in time, is equal to that of the VDollar factor. The VCarry variable is represented in our set of data from January 1997 until June 2015.

3.7 WMKT Factor

To compute the world market equity excess return factor, we use the MSCI World Index, downloaded from DataStream. We compute the end-of-month returns of the using Adjusted Prices from the MSCI World Index and subtract the corresponding 30-day Treasury Bill rate downloaded from Kenneth French's website (French, 2017). The variable is referred to as WMKT.

3.8 LWMKT Factor

Local world market excess return, henceforth LWMKT, is obtained by computing the end-of-month return of the MSCI World Index denominated in each currency in our dataset. We weight each local return equally, and calculate the excess return in excess of the 30-day Treasury Bill rate.

Figure 4
Factor Excess Returns

The figure shows the excess return of the factors in our sample period. The vertical axis denotes annualized excess return (multiplied by 12) in percentages, while the horizontal axis displays the sample period. The horizontal line in each graph represents the sample mean annualized excess return of the factor.

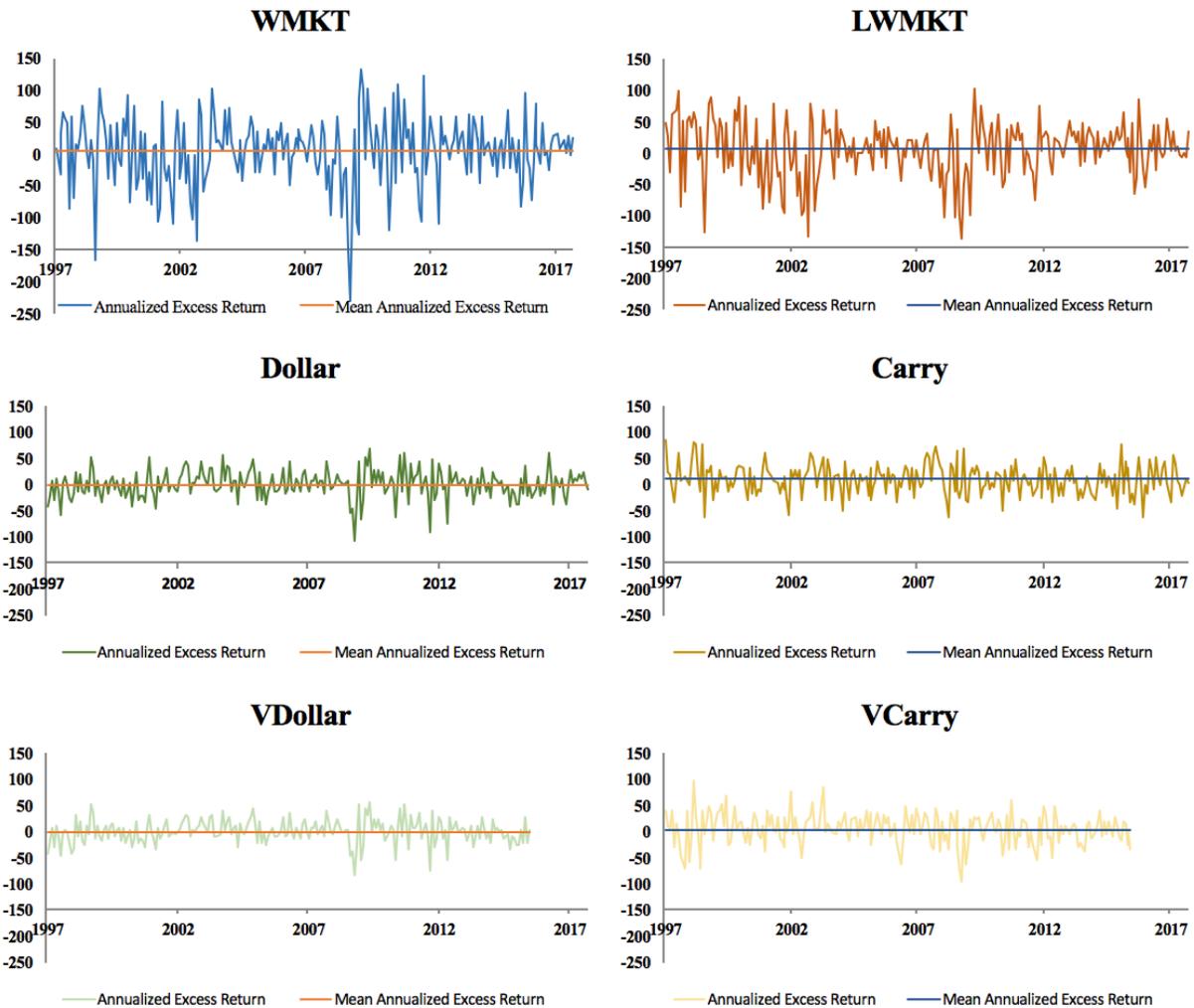


Table 1

Factor Annualized Mean Excess Return and Standard Deviation

The tables show the annualized mean excess return, μ , and standard deviation, σ . All excess returns are in percentage points. The upper table is constructed for the sample period January 1997 to June 2015, while the lower table is constructed for the sample period January 1997 to September 2017.

		Factors					
Moments		WMKT	LWMKT	Dollar	Carry	VDollar	VCarry
μ		4.88	3.05	0.00	9.72	0.17	4.19
σ		44.69	54.40	26.54	28.21	22.12	29.12

		Factors			
Moments		WMKT	LWMKT	Dollar	Carry
μ		5.11	3.43	0.07	9.39
σ		43.63	52.81	25.99	28.37

3.9 Limitations to Our Set of Data

The cross-section of currencies we use for constructing the Dollar and Carry variables contains fewer currencies than similar studies, such as Lustig, et al. (2011) and Brusa, et al. (2014). This is mainly due to our data availability of forward rates. We include the VDollar and VCarry variables to control for this fact. The VDollar and VCarry sample periods end in June 2015 as opposed to September 2017 for the Dollar and Carry factors.

As figure 4 and table 1 show, the Dollar and VDollar factors show similar returns over time, which is underlined by their correlation coefficient of 0.98 (see table 2). Their mean annualized returns differ (0.00% and 0.17% respectively from January 1997 to June 2015) and so do the sample standard deviations (26.54% and 22.12% respectively). The correlation coefficient of the Carry and VCarry variables is 0.51, as shown in table 2, which is lower than for Dollar and VDollar. We cannot be certain why the carry trade risk factors deviate, but the currency cross-sections we use for constructing the variables differ from Verdelhan's, which might lead to different currencies being represented in investment (high interest rate) and funding (low interest rate) portfolios.

The MSCI World stock market index is denoted in US Dollars. Thus, the WMKT factor might, in addition to equity return, contain some currency return. Table 2 displays the correlation between our independent variables, which shows that, in particular, the correlations between the WMKT and Dollar factor and the WMKT and VDollar factor are over 0.5 for both sample periods in our set of data.

We construct the LWMKT using currency data available to us, which represents a smaller cross-section than similar studies. The MSCI World Index returns denominated in local currencies are equally weighted when averaged, which might cause the variable to over- or underweight the contribution of certain currencies.

ETFs are a relatively new type of investment products, which limits the length of time of our data set.

Table 2
Correlation Diagram of Independent Variables

The table shows the sample correlation between our explanatory variables. The sample period is presented above the tables.

<i>January 1997 - June 2015</i>						
	LWMKT	WMKT	Dollar	Carry		
LWMKT	1.00	0.88	0.11	0.19		
WMKT	0.88	1.00	0.57	0.25		
Dollar	0.11	0.57	1.00	0.20		
Carry	0.19	0.25	0.20	1.00		

<i>January 1997 - September 17</i>						
	LWMKT	WMKT	Dollar	Carry	VDollar	VCarry
LWMKT	1.00	0.88	0.13	0.18	0.12	0.37
WMKT	0.88	1.00	0.57	0.24	0.56	0.44
Dollar	0.13	0.57	1.00	0.20	0.98	0.30
Carry	0.18	0.24	0.20	1.00	0.17	0.51
VDollar	0.12	0.56	0.98	0.17	1.00	0.31
VCarry	0.37	0.44	0.30	0.51	0.31	1.00

4. Methodology

We use the Fama-MacBeth procedure (Fama and MacBeth, 1973) to examine the risk compensation of our equity and currency factors². In this section, we present the theoretical background for the Fama-MacBeth procedure and how we apply it to our data. We briefly present regressions expressed in matrix form and the statistical interpretation of pricing errors in excess return models, which we apply to present the “GRS” F-test (Gibbons, Ross and Shanken, 1989) and Shanken-corrected standard errors (Shanken, 1992).

4.1 Fama-MacBeth Procedure

The Fama-MacBeth procedure is an empirical asset pricing exercise originated by Fama and MacBeth (1973). It is a procedure for running cross-sectional regressions and calculating standard errors that correct for cross-sectional correlation in a panel (Cochrane, 2005). If the right-hand variables do not vary over time, the Fama-MacBeth procedure is numerically equivalent to pooled OLS regression (Cochrane, 2005). Thus, Fama-MacBeth t-statistics will differ from pooled OLS regression t-statistics if the right-hand variables vary over time, as the right-hand variables in our set of data do.

To perform Fama-MacBeth cross-sectional regressions, we first estimate the betas using time-series regressions. Fama and Macbeth (1973) use 5-year rolling windows. We estimate the time-series regressions unconditionally (full sample betas) and with 32-, 48-, 60- and 72-month rolling windows.

We have two equity risk factors and two pairs of currency factors in our set of data, namely the equity factors WMKT and LWMKT, and the currency factor pairs Dollar and Carry and VDollar and VCarry. We perform the Fama-MacBeth procedure using one equity factor and one pair of currency factors for each of our models. Because of data availability of the VDollar and VCarry factors, we have two different sample periods. Thus, we perform the Fama-

² To perform rolling windows-regressions and Fama-MacBeth cross-sectional regressions, we use Stata, particularly the *asreg* package downloaded from the Boston College Statistical Software Components (SSC) archive. We believe that there is an error in the package. When using the *asreg* function, names of the coefficient results are returned in the order you type in your *asreg* command, while the values of the coefficients are returned in the order (from left to right) the variables are listed in your Stata data file (.dta). This causes coefficient values to be assigned to the wrong variable names. The possible error in the package does not affect any results presented in our thesis.

MacBeth procedure on six different sets of regressions. We do so by performing two-pass Ordinary Least Squares (OLS) regressions, where the first step consists of time-series regressions on the factors and the second step consists of cross-sectional regressions on the one-period lagged factor betas.

4.1.1 Time-Series Regressions

In the first step, we perform time-series regressions to estimate the factor loadings. In the example-regression, we use LWMKT as the equity factor and Dollar and Carry as the currency factor pair. ETF_t^i represents the excess return of ETF i in period t .

$$ETF_t^i = \alpha_i + \beta_{i,LWMKT} \cdot LWMKT_t + \beta_{i,Dollar} \cdot Dollar + \beta_{i,Carry} \cdot Carry + e_i \quad (6)$$

We express our regressions unconditionally, but we perform both unconditional and conditional time-series regressions. The conditional regressions are performed using rolling windows, which enables time-varying quantities of risk. To show the importance of time-variation in factor loadings, we also perform unconditional time-series regressions. In each rolling window, beta magnitude varies cross-sectionally. Across rolling windows, beta magnitude varies over time for each test asset. In the case of 60-month rolling windows, the first rolling window is the time-period of month 1 – 60, or more generally: The rolling window starts in period $T-59$ and ends in period T . This causes some ETF excess returns to be left out of our set of data, depending on the size of rolling window and sample period. We operate with two panels: January 1997 through June 2015 and January 1997 through September 2017. For both sample periods, we estimate factor loadings unconditionally and using 36-, 48-, 60- and 72-month rolling windows.

After performing the time-series regressions, the length of the data set is shortened according to the length of the rolling windows, T . For example, in the case of rolling window size of $T = 60$ months, the first 59 monthly observations are eliminated from our data set, as the information of this time period is stored in the first 59 rolling window betas.

Evaluating the statistical significance of the first-stage regressions in two-pass regression procedures is important, as newer research shows that there is reason to doubt the results of

second-stage results in the case of statistically insignificant first-stage results (Bryzgalova, 2015). To obtain t-statistics corrected for autocorrelation, we use Newey-West standard errors. Autocorrelation, or serial correlation, is the occurrence of covariance between error terms across time in time-series or panel regressions. In the case of autocorrelation, standard errors are wrong and underestimated. Newey-West standard errors correct for autocorrelation by using a covariance matrix that is heteroscedasticity and autocorrelation consistent (Newey and West, 1987). Relevant academic papers, such as Brusa et al (2014) and Lustig et al (2011), both use Newey-West standard errors to correct for autocorrelation when estimating the time-series betas. We use Newey-West standard errors with one lag.

4.1.2 Cross-Sectional Regressions

In the second step of the Fama-MacBeth procedure, we perform a cross-sectional OLS regression for each cross-section in our set of data. We use the factor loadings estimated in the first step as factors in our cross-sectional regressions. The factor loading on the betas, the lambdas, are estimations of the price of risk. We estimate the price of risk as the average value of lambda. To account for the fact that our betas are estimated factor loadings, we use Shanken-corrected standard errors to determine the statistical significance of the prices of risk (Shanken, 1992). The regression performed for each cross-section is:

$$E_T(ETF_{t+1}^i) = \alpha_t + \lambda_{t,LWMKT} \cdot \beta_{i,LWMKT} + \lambda_{t,Dollar} \cdot \beta_{i,Dollar} + \lambda_{t,Carry} \cdot \beta_{i,Carry} + e_t$$

$i = 1, 2, \dots, N$ for each t (7)

Where $E_T(ETF_{t+1}^i)$ is the sample mean of the ETF return of the rolling window in period $t+1$ for ETF i . The estimates for λ and α_i are computed as the average of the cross-sectional regression estimates:

$$\hat{\lambda} = \frac{1}{T} \sum_{t=1}^T \hat{\lambda}_t; \hat{\alpha}_i = \frac{1}{T} \sum_{t=1}^T \hat{\alpha}_{it}$$
(8)

Furthermore, standard errors are computed as the standard deviations of the cross-sectional regression estimates:

$$\sigma^2(\hat{\lambda}) = \frac{1}{T^2} \sum_{t=1}^T (\hat{\lambda}_t - \hat{\lambda})^2; \quad \sigma^2(\hat{\alpha}_i) = \frac{1}{T^2} \sum_{t=1}^T (\hat{\alpha}_{it} - \hat{\alpha}_i)^2 \quad (9)$$

We use Shanken-corrected Fama-MacBeth standard errors for determining statistical significance of risk prices, which we discuss in greater detail in section 4.3.

4.2 OLS in Matrix Form

We present a brief theoretical explanation of OLS regressions in appendix C. We express OLS in matrix form, as we find it useful for explaining the theoretical background for our GRS-tests and Shanken-corrected standard errors. The estimates of a cross-sectional regression, with betas obtained from a time-series regression, can be expressed as follows (Cochrane, 2005):

$$\hat{\lambda} = (\beta' \beta)^{-1} \beta' E_T(R^e) \quad (10)$$

$$\hat{\alpha} = E_T(R^e) - \hat{\lambda} \beta \quad (11)$$

Where β is the matrix of all betas, β' is the transposed beta-matrix and $E^T(R^e)$ is the vector of sample means of the test asset returns. α is the vector of estimated intercepts and λ is the vector of estimated prices of risk. The variance of the cross-sectional OLS estimates can be expressed as:

$$\sigma^2(\hat{\lambda}) = \frac{1}{T} (\beta' \beta)^{-1} \beta' \Sigma \beta (\beta' \beta)^{-1} \quad (12)$$

$$cov(\hat{\alpha}) = \frac{1}{T} (I - \beta (\beta' \beta)^{-1} \beta') \Sigma (I - \beta (\beta' \beta)^{-1} \beta') \quad (13)$$

Where Σ is the variance-covariance matrix of the estimated residuals and I is the identity matrix.

4.3 Shanken-Corrected Standard Errors

Fama-MacBeth standard errors do not include corrections for the fact that the betas are estimated (Cochrane, 2005). Therefore, for our empirical analyses, we will use Shanken-corrected standard errors (Shanken, 1992) for our estimated lambdas. Shanken-correction of OLS standard errors are calculated as in equation (14) (Cochrane, 2005).

$$\sigma^2(\hat{\lambda}_{OLS}) = \frac{1}{T} (\beta' \beta)^{-1} \beta' \Sigma \beta (\beta' \beta)^{-1} (1 + \lambda' \Sigma_f^{-1} \lambda) + \Sigma_f \quad (14)$$

Comparing equation (14) to equation (12), the Shanken-correction includes a multiplicative correction $(1 + \lambda' \Sigma_f^{-1} \lambda)$ and an additive correction Σ_f , where λ is the vector of risk prices and Σ_f is the variance-covariance matrix of the factors. We calculate our Shanken-correction of the Fama-MacBeth standard errors as follows:

$$\sigma^2(\hat{\lambda}) = \frac{1}{T^2} \sum_{t=1}^T (\hat{\lambda}_t - \hat{\lambda})^2 (1 + \lambda' \Sigma_f^{-1} \lambda) + \frac{\Sigma_f}{T} \quad (15)$$

4.4 Pricing Error

The pricing error is the difference between the actual expected return and the predicted expected return (Cochrane, 2005). Thus, the pricing error for a single factor is the difference of the sample mean of the factor and the product of the factor loading and the factor sample mean. The pricing error of an excess return regression is proportional to the α , or the intercept, of the regression.

4.5 GRS F-tests

The GRS F-test (Gibbons, Ross and Shanken, 1989) is a test of the joint significance of the N pricing errors (α) in a time-series regression, where N is the number of test assets in the cross-section. It is a test for a finite sample, where excess returns and error terms are assumed normal

and independent and identically distributed (Cochrane, 2005). The null hypothesis is that the pricing errors are jointly zero. The GRS test statistic is calculated as follows:

$$\frac{T - N - 1}{N} \left[1 + \left(\frac{E_T(f)}{\hat{\sigma}(f)} \right)^2 \right]^{-1} \hat{\alpha}' \hat{\Sigma}^{-1} \hat{\alpha} \sim F_{N, T-N-1} \quad (16)$$

Where T is the number of time periods in a single time-series regression, N is the size of the cross-section, $E_T(f)$ is the sample mean vector of the factors, $\hat{\sigma}(f)$ is an unbiased estimate of variance-covariance matrix of the factors, α is the pricing error vector, and α' is the transposed pricing error vector. We use the GRS F-test to test the joint significance of the pricing errors, and thus also the performance, of our time-series regressions for each rolling window.

Having discussed how we test our data, we turn to the results of our analyses.

5. Results

In this section, we present the results and performance of our two-pass regression procedure, which we discuss in greater detail in section 6. We examine the performance of our regressions through a variety of tests and visualizations. For the different time-series regressions, we examine the magnitude and significance of factor loadings, and plot the actual expected return versus the predicted expected return to visualize pricing errors for each explanatory variable in the time-series regressions. We use the same framework to compare our model specifications to models containing solely an equity factor. We test joint pricing errors and evaluate our models through the “GRS” F-test. For the cross-sectional regressions, we present economic and statistical significance of our risk price estimates.

5.1 The Magnitude of Factor Loadings

We report the time-variation in magnitude of betas by their minimum, maximum and average value, as shown in figure 5. A positive (negative) loading on the equity factor implies that the ETF excess return co-varies positively (negatively) with the factor, while a loading of zero indicates no covariance.

The average loadings on the WMKT and LWMKT factors generally lie between 0.5 and 1.5, with some outliers. New Zealand in particular loads lower than the other countries, with an average beta just above 0 on both equity factors. Across models, minimum, maximum and average values of the equity factor loadings are similar for all countries.

The economic significances of beta loadings on the Dollar factor differ on several occasions, depending on the equity factor included in the regression. The average Dollar beta value is lower for all countries except New Zealand in the WMKT regression compared to the LWMKT regression. Furthermore, seven minimum values of the Dollar factor loadings are negative in the former regression set, while one in the latter. This is true for both time periods: December 2001 to June 2015 and December 2001 to September 2017. Comparing the regression sets, the magnitudes and time-variation of the Dollar betas varies within countries, but Mexico, New Zealand, Singapore, South Korea and Spain show particularly high time-variation in Dollar loadings. Although slightly different, the loadings on the VDollar factor

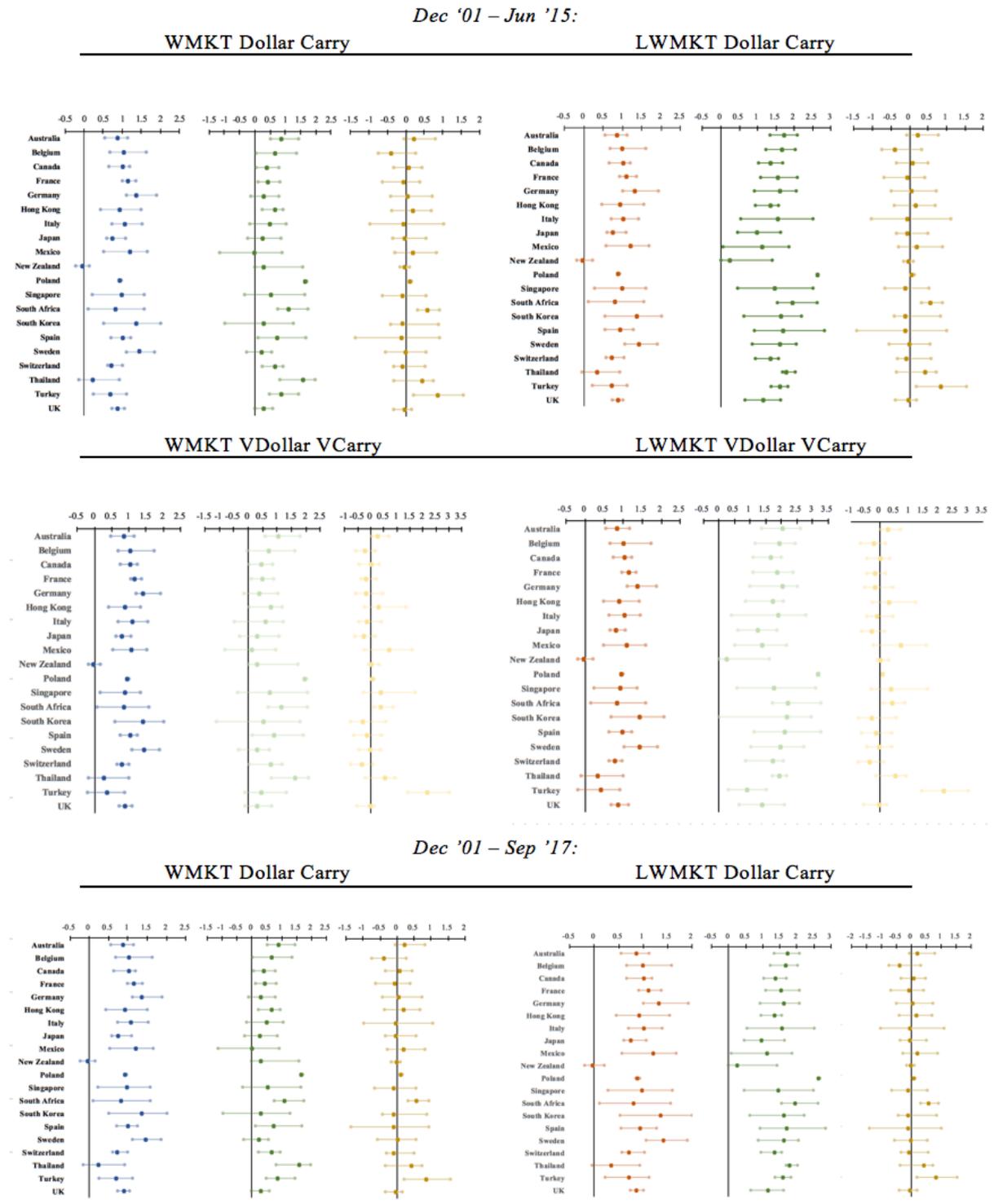
show similar characteristics to those on the Dollar factor. In particular, the magnitude of minimum, average and maximum values are higher when regressed with the LWMKT factor than with the WMKT factor.

The ETF excess returns of the typical carry trade funding countries Japan and Switzerland show Carry factor loadings around zero, in contrast to the notion that currencies traditionally considered carry trade funders would be expected to load negatively on average. Most Euro area countries also load around zero, whereas the ETF returns of Turkey, a country with high nominal interest rates recent years, loads highest on average. The choice of equity factor does not generate much intra-country difference in Carry factor loadings.

The VCarry factor loadings differ from the Carry loadings. Notably, Singapore displays a positive average VCarry loading, while negative average carry loadings on the Carry factor. However, Singapore's VCarry and Carry loadings switch sign over time, which indicates that they are not statistically different from zero. Compared to the other variables, there are more loadings in the Carry and VCarry factors where the minimum and maximum values switch sign over time.

Figure 5
Time-Varying Factor Loading Magnitude

The figure reports magnitude of time-varying factor loadings estimated using 60-month rolling window time-series regressions. The header displays the regression model. ETFs are identified in the horizontal axis by name of the national index they are tracking. The left, middle and right dots in each graph represent minimum, average and maximum factor loading respectively.



5.2 Time-Varying Share of Statistically Significant Factor Loadings

We find that the share of statistically significant betas differs over time when we perform rolling windows-regressions. We illustrate this by graphing the share of statistical significance in factor loadings in each rolling window-regression throughout our set of data. The time-variation obtained by using 60-month rolling windows is shown in figure 6.1 and figure 6.2. As a robustness measure, appendix D.1 and D.2 shows that the time-variation for 36-month rolling windows is similar to the time-variation for 60-month rolling windows.

As illustrated in figure 6.1 and 6.2, we find that the loadings on the equity factors, WMKT and LWMKT, are statistically significant throughout most of the time-series. Common to both factor loadings, the significance share decreases somewhat after June 2013. Comparing regressions containing different explanatory equity factors, but within the same sizes of time-series and cross-sections in test assets, there are notable differences in significance in the Dollar factor loadings. The LWMKT regressions yield a much higher share of significant Dollar factor coefficients than the WMKT regressions. The Carry factor loadings show a lower significance share than the other coefficients, but are less affected by the choice of equity factor.

We also substitute the currency factors, Dollar and Carry, with the currency factors VDollar and VCarry in the time-period from December 2001 to June 2015. Introducing the latter currency factors yields similar results as for the former currency factors. The equity factor loadings, whether on WMKT or LWMKT, show high significance shares throughout the time period, but the significance share is lower and more volatile after June 2013. The share of significant VCarry factor loadings is generally lower than for the equity coefficients and VDollar coefficient. It varies slightly depending on the choice of equity factor, in particular the VCarry significance share is higher during the financial crisis of 2008 when regressed with the WMKT variable. The VDollar factor loading, like the Dollar factor loading, varies depending on the equity factor. For most periods in time, the significance share of VDollar loadings in the LWMKT model is at least fifty percentage points above the WMKT model.

Figure 6.1

Time-Varying Share of Significant Betas

The figure shows how the share of significant betas varies over time for the sample period December 2001 to June 2015. Betas are estimated using 60-month rolling windows. For each regression set, the sample period and independent variables are presented above the graphs. The graphs show the significance share of for each estimated coefficient. The vertical axis shows the percentage of significant betas, while the horizontal axis shows the timeline.

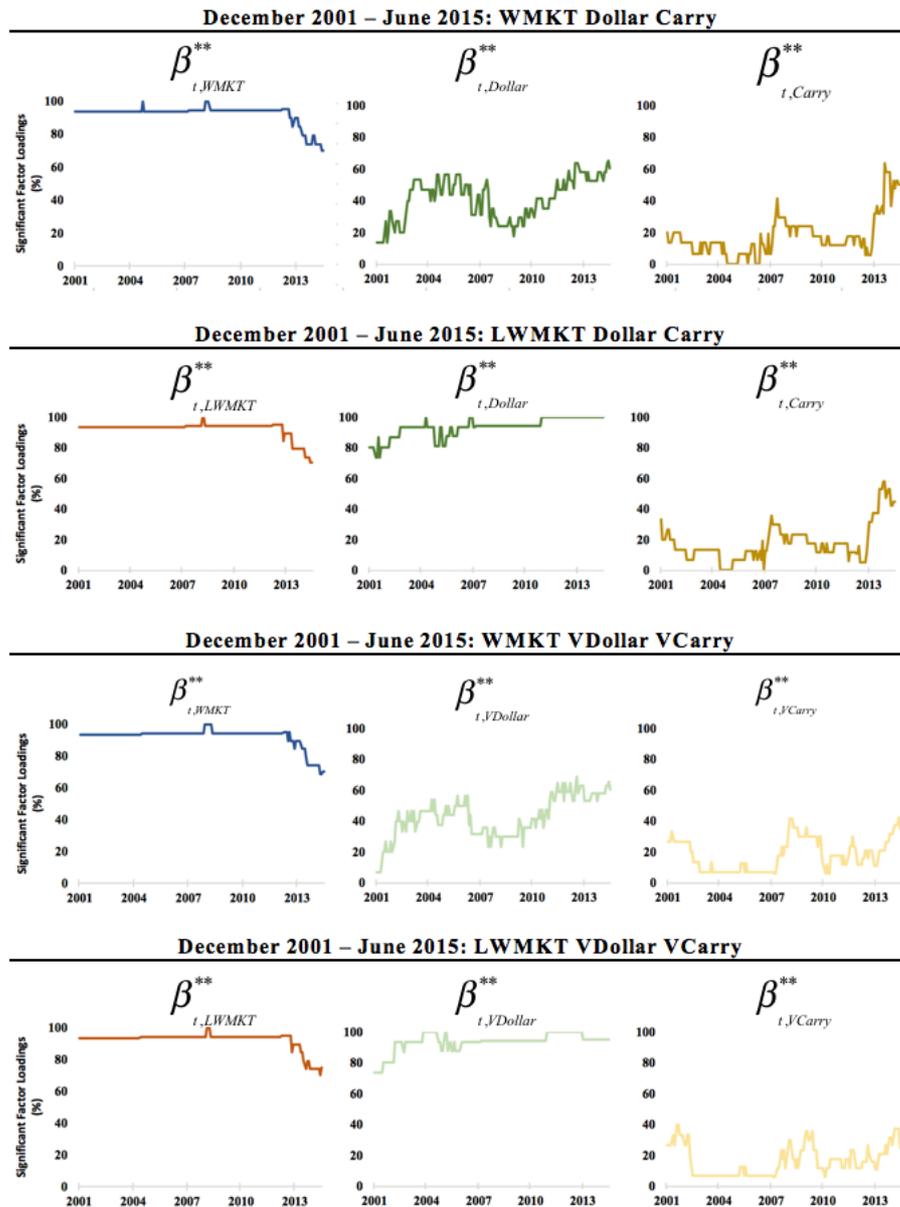
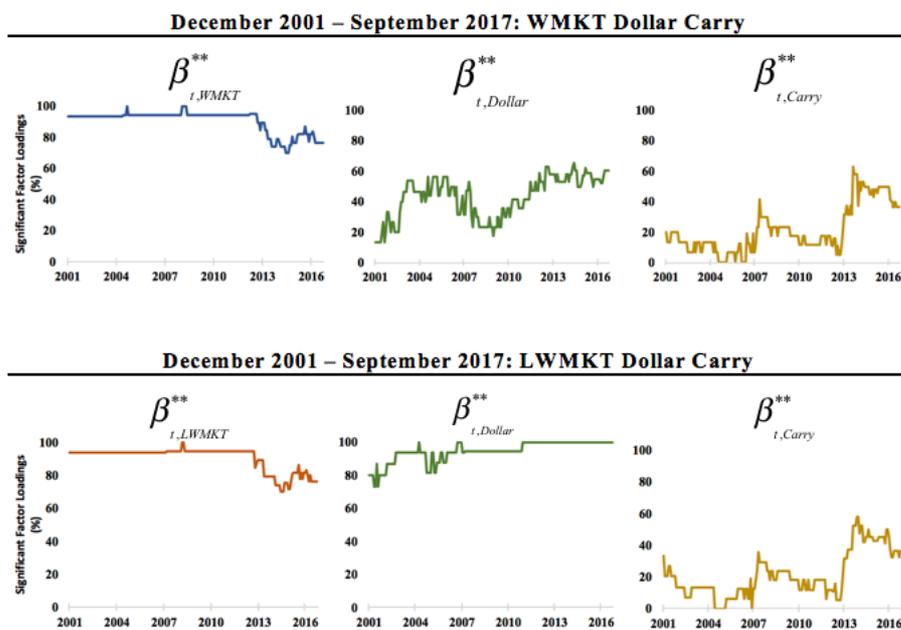


Figure 6.2

Time-Varying Share of Significant Betas

The figure shows how the share of significant betas varies over time for the sample period December 2001 to September 2017. Betas are estimated using 60-month rolling windows. For each regression set, the sample period and independent variables are presented above the graphs. The graphs show the significance share of for each estimated coefficient. The vertical axis shows the percentage of significant betas, while the horizontal axis shows the timeline.



5.3 Realized Excess Return versus Predicted Excess Return

We show the difference between the realized and predicted excess return for our test assets and for our explanatory variables to illustrate the magnitude of pricing errors in our models. Figure 7 shows the deviations between mean realized and predicted ETF excess return for models containing only an equity factor and for the WMKT Dollar Carry and LWMKT Dollar Carry models. Figure 8 maps the deviations between mean realized and predicted excess returns for our explanatory variables. In both figures, results lying close to (far from) the 45-degree line indicate small (big) pricing errors.

Figure 7 shows that pure equity models have lower magnitudes of pricing errors than the models with both equity and currency risk factors. Although the figure does not take statistical significance of the pricing errors into account, it indicates that the pure equity models perform better in explaining ETF excess returns.

Figure 8 shows that for all models, the equity factor WMKT or LWMKT are mapped closely to the 45-degree line, while the pricing errors of the currency factors are bigger. The Dollar returns are spread on both sides of the 45-degree line, nearly unaffected by the choice of equity factor, while the VDollar returns are deviating more from the 45-degree line when in a LWMKT model than when in a WMKT model. The Carry and VCarry factors are situated under the 45-degree line, possibly indicating upwardly biased estimates when the Carry or VCarry factor is regressed alongside LWMKT as the equity excess return factor. In all models, all currency factors display some big deviations from the 45-degree line.

Figure 7

Realized versus Predicted Returns in Test Assets

The figure shows pricing errors for each ETF excess return, estimated using 60-month rolling windows. The upper graphs display pricing errors of models which include solely an equity factor as independent variable, while the lower graphs display pricing errors which are estimated using both equity and currency risk factors. The headers of the graphs specify the independent variables in each model. The realized mean excess return is calculated as follows: 1) rolling window excess returns of each test asset is averaged, 2) the rolling window averages are averaged. The predicted excess return is calculated as follows: 1) rolling window excess returns for each test asset is averaged, 2) rolling window factor means are multiplied by their estimated factor loadings and the products are added, 3) the sums of the rolling window products of factor means and betas are averaged.

Results lying close to (far from) the 45-degree line indicate small (big) pricing errors.

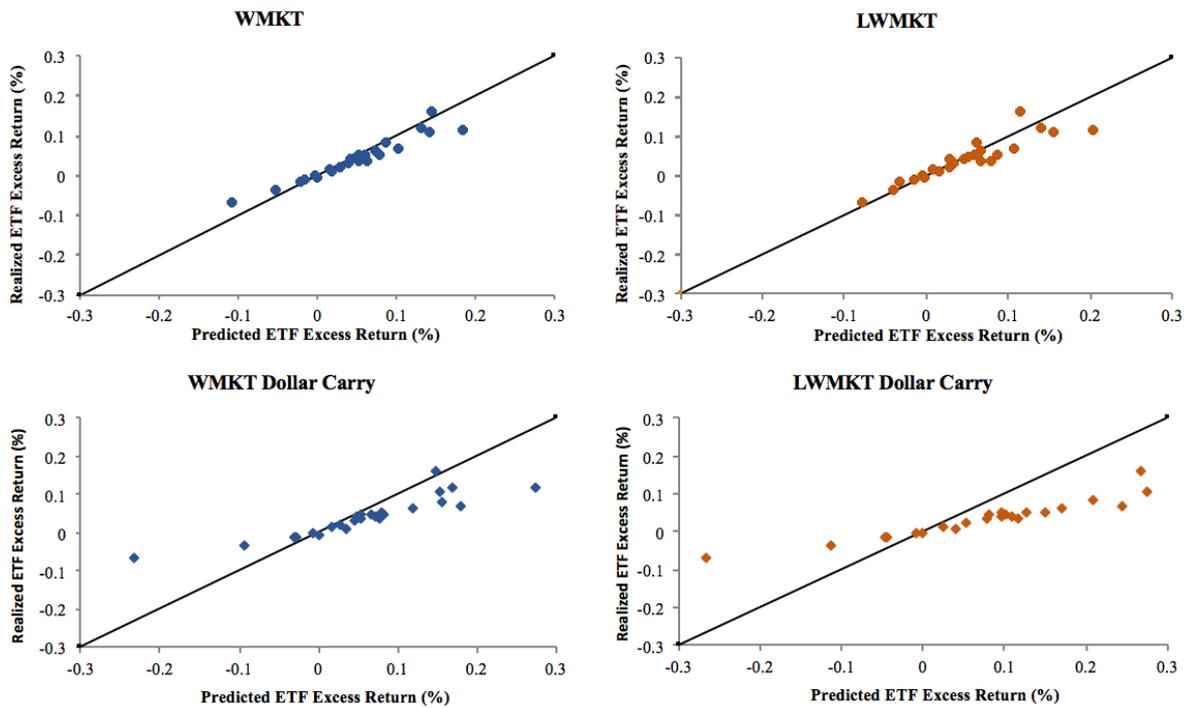
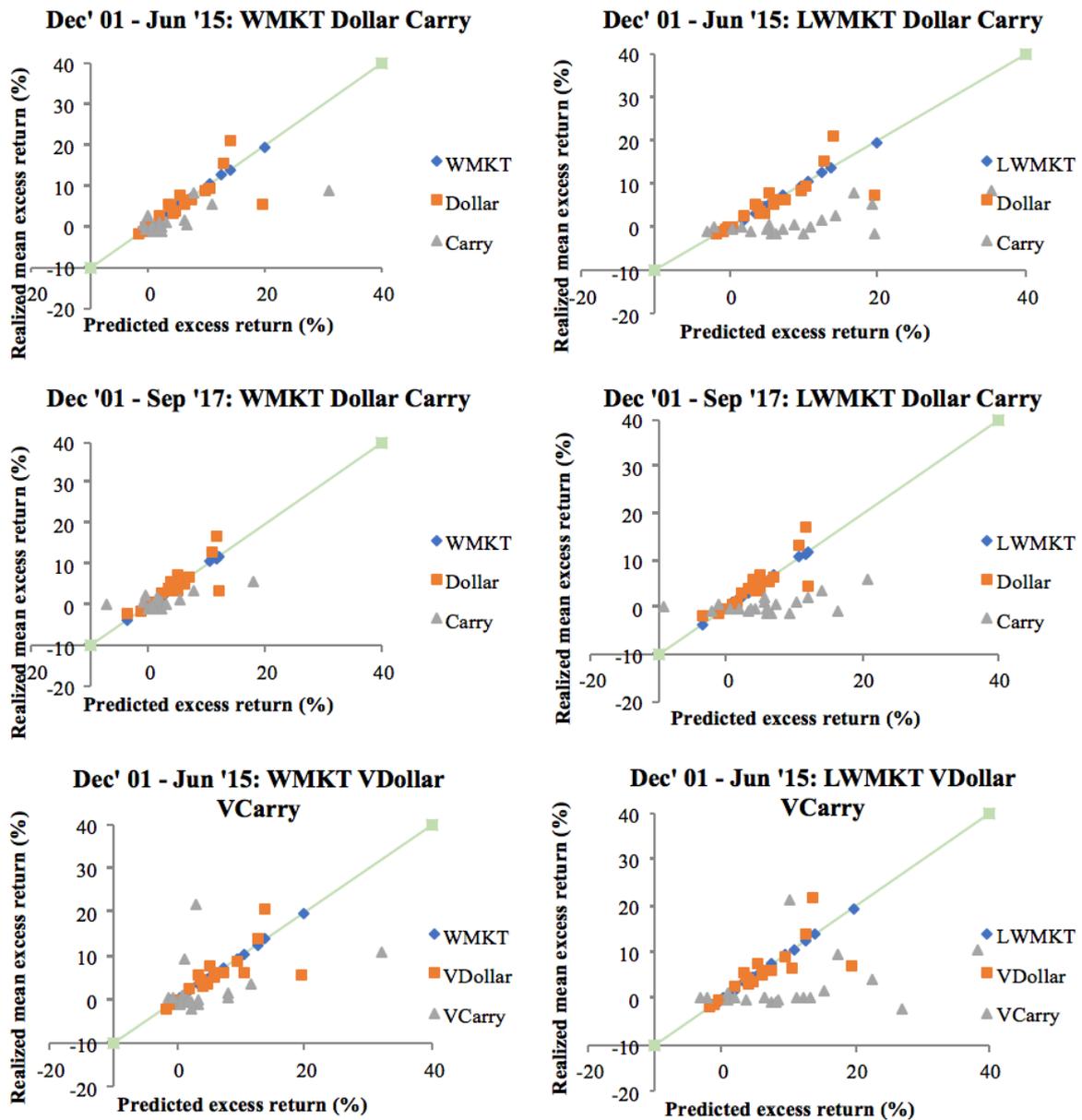


Figure 8

Realized versus Predicted Returns in Independent Variables

The figure shows pricing errors for each explanatory variable in our models estimated using 60-month rolling windows. The realized mean excess return is calculated as follows: 1) rolling window excess returns of each factor is averaged, 2) the rolling window averages are averaged. The predicted excess return is calculated as follows: 1) rolling window excess returns for each factor is averaged, 2) rolling window factor means are multiplied by their estimated factor loadings, 3) the rolling window products of factor means and betas are averaged. Results lying close to (far from) the 45-degree line indicate small (big) pricing errors.



5.4 “GRS” F-test

The GRS-test tests the joint significance of the pricing errors in each rolling window, where the null hypothesis is that the pricing errors are jointly zero. Our results show that pricing errors are notably significant in all models, as shown in table 3. We compare our models to models including only an equity factor, both WMKT and LWMKT. The models which contain equity and currency factors display notably lower shares of jointly significant pricing errors than models which contain solely an equity factor. The currency models which use either WMKT or LWMKT as their equity risk factor display over 20 percentage points lower shares of jointly significant pricing errors than their corresponding equity model, for both sample periods.

The currency models containing WMKT as the equity factor perform better than the LWMKT currency models, and the VDollar VCarry models perform better than the Dollar Carry models.

The timeline of null rejection, shown in figure 9, shows that all models contain jointly significant pricing errors for longer periods of time. The period between August 2005 and November 2010 the WMKT Dollar Carry and LWMKT Dollar Carry models contain only jointly significant alphas. Additionally, the currency models containing the LWMKT factor display jointly significant pricing errors between December 2001 and July 2003. The equity risk models, WMKT and LWMKT, generate jointly significant pricing errors from December 2013 to September 2017.

Table 3

% of Rolling GRS-test Rejecting the Null

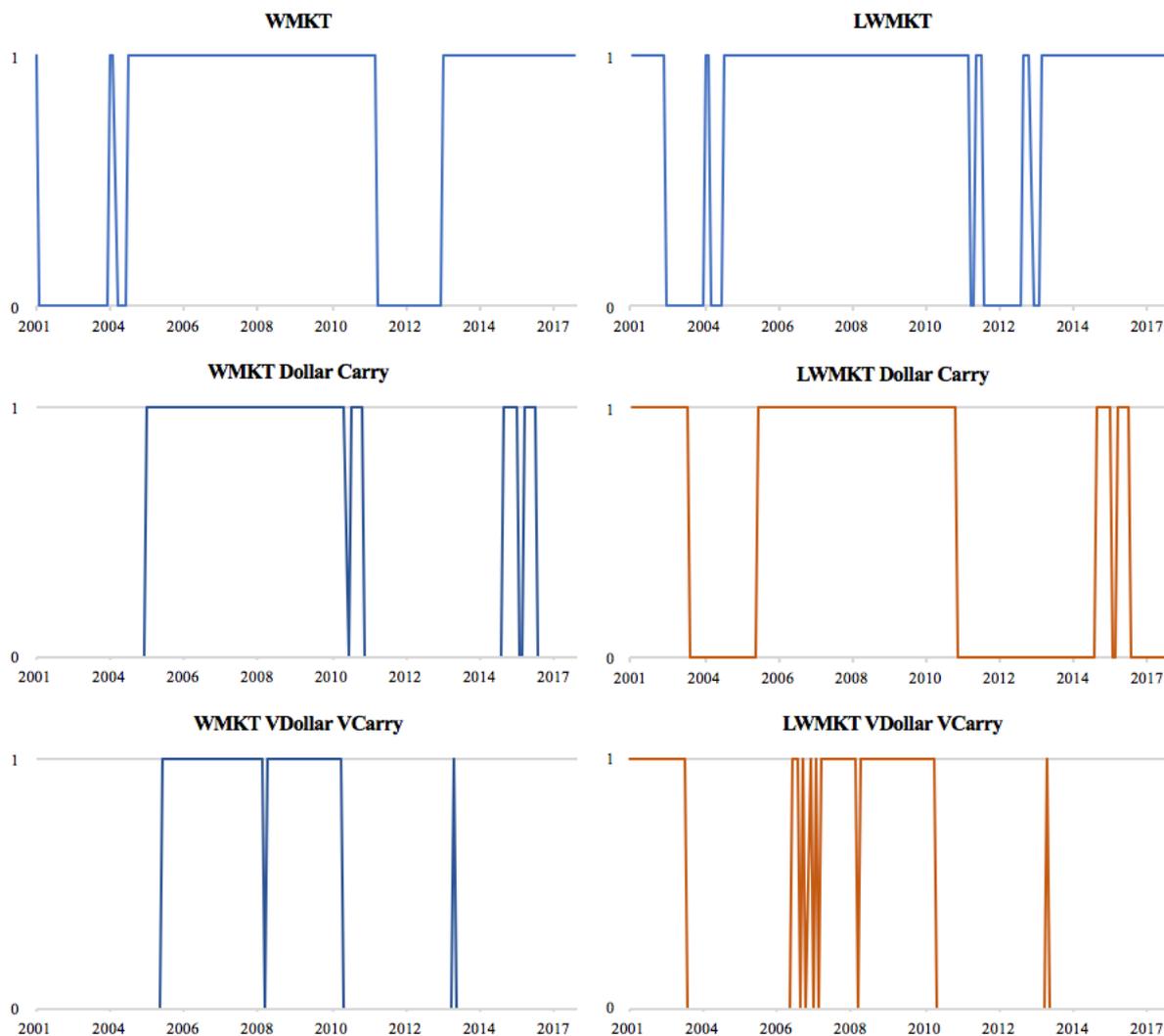
The table reports the results of the GRS F-tests. A GRS-test as described in section 4.5 is performed on each rolling window. The table reports the share of jointly significant alphas for each regression set.

Model	% of Rolling GRS-test Rejecting the Null
<i>Dec '01 - Jun '15</i>	
WMKT	68.10%
LWMKT	77.30%
WMKT Dollar Carry	46.01%
LWMKT Dollar Carry	55.83%
WMKT VDollar VCarry	39.26%
LWMKT VDollar VCarry	41.10%
<i>Dec '01 - Sep '17</i>	
WMKT	72.63%
LWMKT	80.53%
WMKT Dollar Carry	44.74%
LWMKT Dollar Carry	53.16%

Figure 9

Timeline of Jointly Significant Alphas

The figure shows in what time periods the “GRS” F-test rejects the null hypothesis that pricing errors are jointly zero. A value of 1 (0) indicates jointly significant (jointly zero) alphas.



5.5 Cross-Sectional Regressions and Prices of Risk

We run the cross-sectional regressions and compute the prices of risk as described in section 4.1.2. Table 4.1 and 4.2 display the risk price estimates along with Shanken-corrected standard errors. We present the statistical and economic significance of the results in the following paragraphs.

We find that for all models, neither equity risk nor currency risk is priced when estimated unconditionally. Additionally, the mean absolute errors and root mean squared errors are notably higher for the unconditional models. In the conditional models, the Carry and VCarry factors are significant on a 1% level for all models and for all rolling window sizes. The dollar factors, Dollar and VDollar, are never priced on 5% significance level when estimated using 36-month rolling windows, but are with one exception (the second model specification in table 4.1) significant on a 1% level in the time period December 2001 to June 2015 for 48-, 60- and 72-month rolling windows. In the time period December 2001 to September 2017, the Dollar factor is never priced. In conditional models, the price of the WMKT and LWMKT factors are always significant on a 5% level when regressed with the Dollar and Carry factors, while only the WMKT risk price in 60- and 72-month rolling windows is significantly priced in the VDollar and VCarry models.

For the WMKT Dollar Carry and LWMKT Dollar Carry models, from December 2001 to June 2015 with 60-months rolling windows, we find that that an additional unit of exposure to the world market excess return is associated with a 3.64 percentage points increase in expected ETF excess return per annum, while an additional unit of exposure to the local world market excess return is associated with a 2.93 percentage points increase in expected excess return per annum. When regressing the equity factors with the VDollar and VCarry factors, risk prices of both equity factors fall: An additional unit of exposure to the world market excess return yields an increase in excess returns of 1.83 percentage points per annum, while the local world market excess return is no longer priced, so that an additional unit of exposure to it is not associated with an increase in expected ETF excess return. For 60-month rolling windows, in the sample period from December 2001 to September 2017, an additional unit of risk exposure to the WMKT and LWMKT factors is associated with a 2.24 and 2.59 increase respectively in ETF excess return per annum.

Dollar risk is only priced in the shorter panel, between December 2001 and June 2015. In this sample, an additional unit of Dollar risk will yield 1.68 and 0.94 percentage points higher excess return per annum, when regressed with WMKT and LWMKT respectively. An additional unit of VDollar risk exposure is associated with an additional 2.92 and 2.07 percentage points excess ETF return per annum.

The Carry factor is priced in all models, independent of the choice of equity factor and length of time period. For 60-month rolling windows, an additional unit of exposure to the Carry factor is associated with an increase in excess return of 4.67 and 5.99 percentage points in our samples. For the same rolling window size, the VCarry factor is associated with an increase in excess return above 7 percentage points per unit of exposure.

For all rolling window sizes, the price of Carry risk is never higher in a WMKT model than in a LWMKT model, while the price of VCarry risk is always higher in a WMKT model. The price of Dollar and VDollar risk is always higher in a WMKT model than in a LWMKT model. For all equity and currency factors, the price of risk increases with the size of rolling windows.

Table 4.1

Fama-MacBeth Prices of Risk

The table reports the Fama-MacBeth estimates of our cross-sectional regressions for the time period December 2001 to June 2015. The model, or the independent variables used in the regressions, is reported on the left side. Shanken-corrected standard errors are in parentheses. All excess returns are annualized (multiplied by 12) and in percentage points. *, ** and *** report statistical significance on a 10%, 5% and 1% level respectively.

Model		Rolling Window Size				
		None	36	48	60	72
<i>Dec '01 - Jun '15</i>						
WMKT Dollar Carry	λ_{WMKT}	3.97 (5.99)	2.72*** (0.69)	2.83*** (0.62)	3.64*** (0.55)	4.37*** (0.58)
	λ_{Dollar}	-2.38 (5.16)	6.60 (0.47)	1.30*** (0.50)	1.68*** (0.44)	1.15*** (0.34)
	λ_{Carry}	10.48 (28.36)	3.81*** (0.89)	5.02*** (0.96)	5.92*** (0.99)	7.19*** (1.14)
	<i>MAE</i>	84.47	5.63	4.78	4.13	3.59
	<i>RMSE</i>	94.79	6.17	5.48	4.99	4.58
LWMKT Dollar Carry	λ_{LWMKT}	5.90 (8.35)	2.42*** (0.76)	2.46*** (0.66)	2.93*** (0.61)	4.00*** (0.75)
	λ_{Dollar}	-1.78 (4.46)	0.17 (0.42)	0.60 (0.41)	0.94*** (0.34)	0.55** (0.27)
	λ_{Carry}	9.98 (26.11)	3.82*** (0.90)	5.02*** (0.96)	5.99*** (1.02)	7.29*** (1.17)
	<i>MAE</i>	84.43	5.48	4.57	3.88	3.41
	<i>RMSE</i>	94.78	6.22	5.54	5.04	4.62
WMKT VDollar VCarry	λ_{WMKT}	5.26 (6.91)	0.60 (0.64)	0.97* (0.57)	1.83*** (0.52)	3.06*** (0.51)
	λ_{VDollar}	-1.24 (3.77)	0.89* (0.54)	1.80*** (0.66)	2.92*** (0.54)	3.17*** (0.28)
	λ_{VCarry}	3.62 (7.73)	5.78*** (1.29)	6.85*** (1.21)	7.87*** (1.48)	8.65*** (0.37)
	<i>MAE</i>	84.40	5.37	4.21	3.52	2.67
	<i>RMSE</i>	94.78	6.07	5.16	4.61	4.19
LWMKT VDollar VCarry	λ_{LWMKT}	6.28 (9.03)	0.24 (0.76)	-0.10 (0.62)	-0.29 (0.53)	0.61 (0.46)
	λ_{VDollar}	-0.67 (11.34)	0.45 (0.40)	1.13*** (0.42)	2.07*** (0.48)	2.34*** (0.41)
	λ_{VCarry}	3.48 (7.67)	5.39*** (1.12)	6.40*** (1.18)	7.40*** (1.12)	8.31*** (1.40)
	<i>MAE</i>	84.41	5.41	4.12	3.30	2.44
	<i>RMSE</i>	94.78	6.14	5.26	4.73	4.30

Table 4.2

Fama-MacBeth Prices of Risk

The table reports the Fama-MacBeth estimates of our cross-sectional regressions for the time period December 2001 to September 2017. The model, or the independent variables used in the regressions, are reported on the left side. Shanken-corrected errors are in parentheses. All excess returns are annualized (multiplied by 12) and in percentage points. *, ** and *** report statistical significance on a 10%, 5% and 1% level respectively.

Model		Rolling Window Size				
		None	36	48	60	72
<i>Dec '01 - Sep '17</i>						
WMKT Dollar Carry	λ_{WMKT}	2.70 (5.15)	1.88** (0.59)	2.07*** (0.53)	2.24*** (0.52)	2.74*** (0.54)
	λ_{Dollar}	-0.80 (3.58)	-0.21 (0.43)	0.30 (0.42)	0.54 (0.38)	0.21 (0.31)
	λ_{Carry}	9.32 (25.52)	3.17*** (0.72)	3.99*** (0.79)	4.67*** (0.86)	5.89*** (1.03)
	<i>MAE</i>	91.14	5.94	5.08	4.32	3.83
	<i>RMSE</i>	97.30	6.08	5.30	4.77	4.89
LWMKT Dollar Carry	λ_{LWMKT}	5.42 (5.42)	2.49*** (0.72)	2.54*** (0.60)	2.59*** (0.51)	3.27*** (0.57)
	λ_{Dollar}	-0.19 (3.32)	-0.63 (0.41)	-0.30 (0.38)	-0.09 (0.33)	-0.31 (0.27)
	λ_{Carry}	8.80 (23.24)	3.18*** (0.73)	4.00*** (0.78)	4.74*** (0.89)	6.01*** (1.05)
	<i>MAE</i>	91.13	5.80	4.89	4.07	3.65
	<i>RMSE</i>	97.30	6.14	5.35	4.81	4.42

6. Discussion

In this section, we discuss the results presented in section 5.

6.1 The Magnitude of Factor Loadings

The magnitude of minimum, maximum and average exposure to the Dollar and VDollar factor differs depending on the model's equity factor. When regressed in an LWMKT model, the magnitude of Dollar and VDollar factor loadings are considerably higher than in the WMKT models. As shown in table 2, the correlations between WMKT-Dollar and WMKT-VDollar are higher than LWMKT-Dollar and LWMKT-VDollar, which might offer an explanation for the Dollar exposure's sensitivity to which equity factor it is modelled with.

For several ETF excess returns, Carry and VCarry loadings are indistinguishable from zero, by which we mean that their minimum and maximum factor loading values, shown in figure 5, are on different sides of zero. Lustig, et al. (2011) note that the Carry (or VCarry) factor is a slope factor on which high interest rate currencies load positively and low interest rate currencies load negatively. Thus, an ETF which is denominated in a currency with interest rates that in most time periods are between the interest rates of the currencies in the top and bottom portfolios of the Carry risk factor, is likely to load neither positively nor negatively on the Carry factor.

6.2 Time-Varying Share of Statistically Significant Factor Loadings

The share of significant Carry and VCarry factor loadings are notably higher during and after financial crises. In our sample periods, significance peaks around the occurrences of the Dot-Com crash and the financial crisis of 2008, and in 2013, which might be related to the European debt crisis. These results are more pronounced when factor loadings are estimated using 60-month rolling windows (see figure 6.1 and 6.2) than for 36-month rolling windows (see appendix D.1 and D.2), but are present for both rolling window sizes.

Significance for the loadings on the Dollar and VDollar factors is notably higher in WMKT models than in LWMKT models. This might be caused by the correlation between WMKT and the Dollar and VCarry factors.

6.3 Realized Excess Return versus Predicted Excess Return

The realized versus predicted excess return figures map the individual deviations between the actual mean excess return of an ETF (a factor) and its mean excess return predicted by the time-series models, for all test assets (explanatory variables) in all models.

In explaining ETF excess return, pure equity models show less deviations from the 45-degree line than equity and currency models, which suggests that the magnitude of pricing errors is bigger for equity and currency models. Unlike the GRS F-tests, the realized versus predicted excess return figures do not take into account statistical significance of the pricing errors. Thus, the pricing errors of the figures are possibly misleading. In table 4.1 and 4.2, we show that currency risk is priced in our test assets. Thus, the pure equity models might neglect some of the currency risk associated with international ETF investments, and yield pricing errors which, although smaller in magnitude, are wrong.

For all combined equity and currency models including the WMKT factor, the currency factors are situated closer to the 45-degree line, which indicates that the WMKT models perform better than the LWMKT models in predicting currency excess returns. Both equity excess returns are situated closely around the 45-degree line, indicating that the predicted excess equity returns are precise, regardless of equity factor and model. For equal sample periods, the models including VDollar and VCarry factors show bigger deviations from the 45-degree line than the Dollar and Carry models, suggesting that the Dollar and Carry models perform better in predicting currency excess returns.

6.4 GRS F-Tests

The GRS F-tests test the joint significance of alphas for each rolling window. We report the share of alphas, estimated using 60-month rolling windows, which are jointly significant, and offer timelines that illustrate at which points in time the joint significances of pricing errors occur. Compared to similar studies, such as Brusa, et al. (2014), the share of jointly significant alphas is big. Of the models with both equity and currency risk factors, the model with the lowest share is WMKT VDollar VCarry, which includes 39.26% jointly significant alphas. The results cast doubt over how well the models are explaining the ETF excess return. However, comparing the share of jointly significant pricing errors of combined equity and

currency models to models which only contain an equity factor shows that the combined equity and currency models are superior in explaining ETF excess return.

For the equity and currency regression sets, the WMKT models contain less jointly significant alphas than the LWMKT models, and the VDollar and VCarry models less than the Dollar and Carry models. The timelines of GRS-test results show that all models have high occurrences of jointly significant alphas in the time period starting August 2005 and ending November 2010. Jointly significant alphas in the time period starting December 2001 and ending July 2003 is unique to the LWMKT models. The models which contain only an equity variable generate jointly significant alphas from December 2013 throughout the sample periods, as we show in figure 9. As figure 6.1 and 6.2 display, the share of significant factor loadings on Carry and VCarry factors increase in this period. This might point to the Carry trade risk factors' importance in capturing international ETF excess returns.

6.5 Risk Prices

Capturing time-variation in risk prices by estimating our models conditionally is crucial for obtaining statistically significant risk prices and regression models which fit OLS, as the difference in root mean squared error and mean absolute error of the conditional and unconditional models indicates. This is in line with the results of, among others, Jagannathan and Wang (1996) and Brusa, et al. (2014). We find currency risk to be priced in our test assets, as shown in table 4.1 and 4.2. In particular, carry trade risk, for both the Carry and VCarry factor, is associated with higher ETF excess returns in all models and all sample periods.

7. Conclusion

Our thesis evaluates whether U.S. investors are compensated for bearing currency risk in international ETFs.

We conclude that models which combine equity and currency risk factors outperform models of one (equity) factor in explaining ETF excess returns. We find that in our sample, currency risk is priced in international ETFs. We do so using models of three factors, one equity factor and two currency factors, and estimate risk exposure and price conditionally using rolling windows. We find that U.S. investors are compensated for taking currency risk, in particular carry trade risk, regardless of the sample period and rolling window-size we use, but only when we account for time-variation in exposures to and prices of risk.

We believe that our findings have a clear interpretation, which can be useful for international ETF investors. Carry trade risk is priced in international ETFs. The higher the interest rate of the currency of denomination, the more the ETF is exposed to the carry trade risk. Thus, investing in ETFs which are denominated in high interest rate currencies is associated with higher expected return, but also higher systematic risk.

We believe that an interesting topic for further research is to investigate whether currency risk is priced in investment products that are marketed with a currency-hedging strategy. Investment firms are often secretive about how currency hedging strategies are implemented in their investment products. Employing the same methodology as we have in our thesis on a group of test assets that are said to be currency-hedged could shed light on whether and to what degree currency-hedging investment vehicles shield investors from currency risk.

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Appendix

Appendix A

ETF and Currency Data Coverage

The table reports the starting date of ETF returns, spot rates and forward rates along with their sources for each country in our data set. All series end in September 2017. The ETF series are from the New York Stock Exchange Archipelago Exchange (NYSE ARCA) and Nasdaq Stock Market (NASDAQ). The spot- and forward rates' origin are WM/Reuters (WMR) and Thompson Reuters (TR). The currency codes are following the ISO 4217 standards (International Organization for Standardization, 2015).

Country	Code	Equity data set		Currency data set		
		ETF		Spot rates	1m Fwd rates	
		NYSE ARCA	NASDAQ	WMR	TR	WMR
Australia	AUD	Jan. - 97	-	Jan. - 97	-	Jan. - 97
Switzerland	CHF	Jan. - 97	-	Jan. - 97	Jan. - 97	-
Hong Kong	HKD	Jan. - 97	-	Jan. - 97	Jan. - 97	-
Japan	JPY	Jan. - 97	-	Jan. - 97	Jan. - 97	-
Norway	NOK	Feb. - 12	-	Jan. - 97	Jan. - 97	-
Mexico	MXN	Jan. - 97	-	Apr. - 06	Apr. - 06	-
Sweden	SEK	Jan. - 97	-	Jan. - 97	Jan. - 97	-
South Africa	ZAR	Mar. - 03	-	Jan. - 97	Jan. - 97	-
South Korea	KRW	Jun. - 00	-	Apr. - 06	Apr. - 06	-
Spain	ESP	Jan. - 97	-	Jan. - 97	-	Jan. - 97
Belgium	BEF	Jan. - 97	-	Jan. - 97	-	Jan. - 97
Russia	RUB	Dec. - 10	-	May - 06	May - 06	-
Canada	CAD	Jan. - 97	-	Jan. - 97	Jan. - 97	-
Czech Republic	CZK	-	-	Jan. - 97	Jan. - 97	-
Denmark	DKK	Feb. - 12	-	Jan. - 97	Jan. - 97	-
France	FRF	Jan. - 97	-	Jan. - 97	-	Jan. - 97
Germany	DEM	Jan. - 97	-	Jan. - 97	-	Jan. - 97
Italy	ITL	Jan. - 97	-	Jan. - 97	-	Jan. - 97

Portugal	PTE	-	-	Jan. - 97	Jan. - 97	-
China	CNY	Apr. - 11	-	May - 06	May - 06	-
Eurozone	EUR	Jul. - 14	-	Jan. - 99	-	Jan. - 99
India	INR	Mar. - 12	-	May 06	May 06	-
Poland	PLN	Jun. - 10	-	Jan. - 97	Jan. - 97	-
Singapore	SGD	Jan. - 97	-	Jan. - 97	Jan. - 97	-
Thailand	THB	Apr. - 08	-	Jan. - 97	Jan. - 97	-
Turkey	TRY	-	Apr. - 08	May - 06	May - 06	-
United Kingdom	GBP	Jan. - 97	-	Jan. - 97	-	Jan. - 97
New Zealand	NZD	Jan. - 97	-	Jan. - 97	-	Jan. - 97

Appendix B

Currency Portfolios sorted by Forward Discount

This table reports summary statistics (mean μ and standard deviation σ) on portfolios of currencies sorted on their forward discount. For each portfolio, summary statistics are reported for the average log forward discount ($f - s$) and the average log excess return $rx_t = (f_{t-1} - s_{t-1}) - \Delta s_t$. All moments are annualized and in percentage points. The sample period is January 1997 to September 2017.

Moments	Portfolios					
	1	2	3	4	5	6
	Forward Discount: $f - s$					
μ	-5.47	-1.46	-0.12	1.12	2.97	9.46
σ	1.63	0.57	0.51	0.52	0.56	1.20
	Excess Return: $rx_t = (f_{t-1} - s_{t-1}) - \Delta s_t$					
μ	-5.12	-1.19	1.04	1.34	1.71	4.78
σ	8.51	7.74	7.66	8.11	8.76	10.47

Appendix C

Ordinary Least Squares Regression (OLS)

Ordinary Least Squares is a simple form of regression, where the objective is to estimate a linear relationship between a dependent variable, the y variable, and one or more independent variables, the x variables. An OLS regression with a single factor is on the form:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 \cdot x + \hat{u} \quad (17)$$

Where \hat{y} is the estimated dependent variable, $\hat{\beta}_0$ is the estimated intercept, $\hat{\beta}_1$ is the coefficient, or the factor loading, on the independent variable x , and \hat{u} is the estimated error term. The model is estimated by minimizing the sum of squared errors.

The goodness of fit of an OLS regression is called R^2 , which is a measure of how well the model fits linear regression (Ubøe, 2007). It measures the sum of squares explained by the model as a share of the total sum of squares in the model.

$$R^2 = \frac{SSE}{SST} = 1 - \frac{SSR}{SST} \quad (18)$$

where SST is the Sum of total squares, SSE is the sum of squares explained by model and SSR is the sum of squared residuals (errors). SST can be expressed as:

$$SST = SSE + SSR \quad (19)$$

which is identical to:

$$\sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 + \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (20)$$

where \bar{y} is the average value of the dependent variable, y_i are the observed values of the dependent variable, and \hat{y}_i are the predicted values of Y for the given x_i value.

RMSE, the root mean squared error, and MAE, the mean absolute error, are two metrics used for evaluating the size of the error term. RMSE is the mean value of root of the sum of squared errors, while MAE is the mean absolute value of the error terms.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y})^2} \quad (21)$$

$$MAE = \frac{1}{n} \left| \sum_{i=1}^n (y_i - \hat{y}) \right| \quad (22)$$

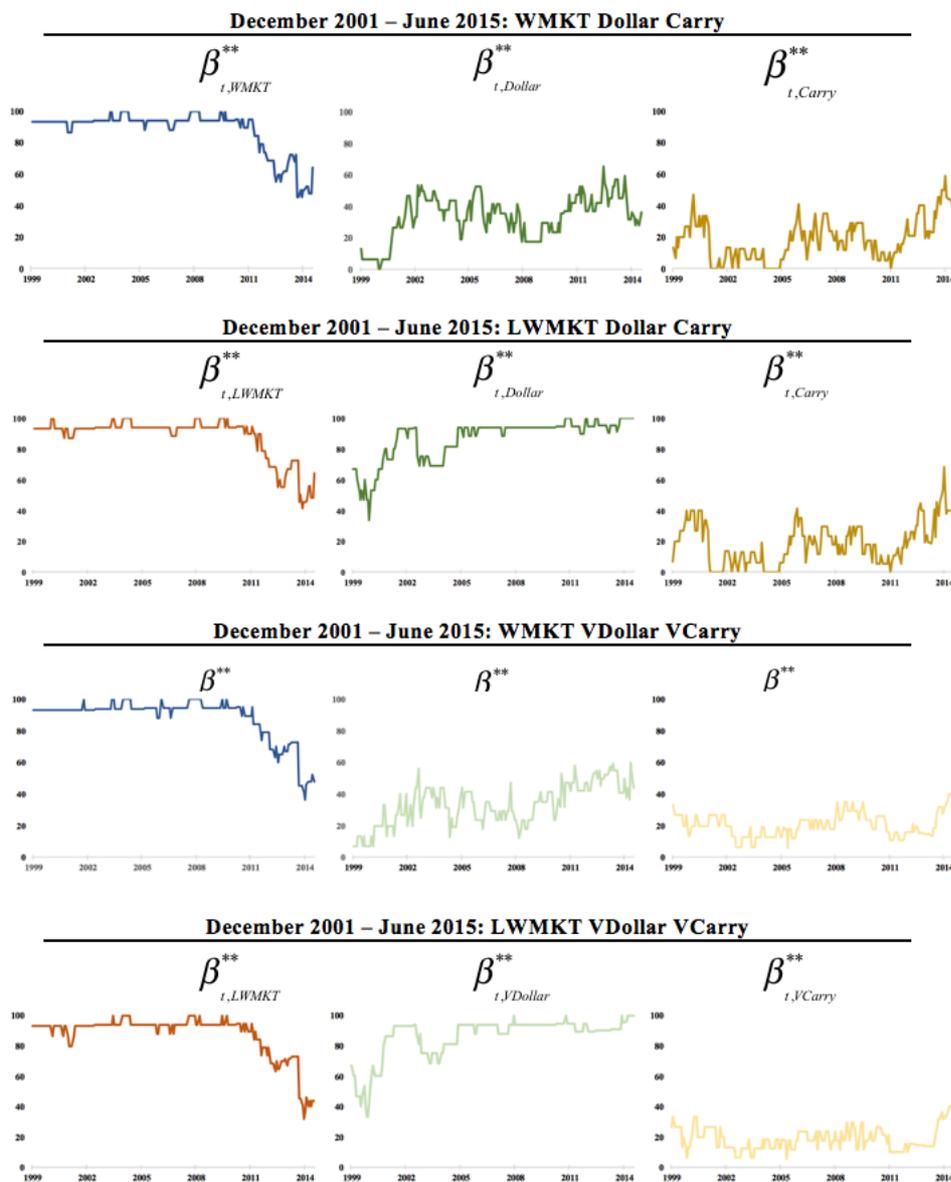
We use RMSE and MAE to evaluate the magnitude of the error terms in our cross-sectional model.

The statistical significance of the estimated coefficients helps determine whether an independent variable co-varies with the dependent variable or not. We measure whether estimated coefficients are significantly different from zero, mainly within a 95% confidence interval. Thus, a coefficient is significantly different from zero if the absolute value of the t-value is larger than 1.96, which is the equivalent of a P-value lower than 5%. We expect readers of our thesis to be familiar with t- and P-values.

Appendix D.1

Time-Varying Share of Significant Betas

The figure shows how the share of significant betas varies over time for the sample period December 2001 to June 2015. Betas are estimated using 36-month rolling windows. For each regression set, the sample period and independent variables are presented above the graphs. The graphs show the significance share of for each estimated coefficient. The vertical axis shows the percentage of significant betas, while the horizontal axis shows the timeline.



Appendix D.2

Time-Varying Share of Significant Betas

The figure shows how the share of significant betas varies over time for the sample period December 2001 to September 2017. Betas are estimated using 36-month rolling windows. For each regression set, the sample period and independent variables are presented above the graphs. The graphs show the significance share of for each estimated coefficient. The vertical axis shows the percentage of significant betas, while the horizontal axis shows the timeline.

