# Global Macro Risks in Currency Excess Returns

Kimberly A. Berg[a] *    Nelson C. Mark[b]

May 2016

**Abstract**

We study the cross-section of carry-trade generated currency excess returns in terms of their exposure to global fundamental macroeconomic risk. The cross-country high-minus-low (HML) conditional skewness of the unemployment gap, our measure of global macroeconomic uncertainty, is a factor that is robustly priced in currency excess returns. A widening of the HML gap signifies increasing divergence, disparity, and inequality of economic performance across countries.

Keywords: Currency excess returns, beta-risk, carry trade, global macro risk.
JEL: E21, E43, F31, G12

[a] Bank of Canada
[b] Department of Economics, University of Notre Dame and NBER

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*Corresponding author, Kimberly A. Berg, Bank of Canada. The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Bank of Canada. This paper has benefited from presentations at American University, the Bank of Canada, the 2015 Canadian Economic Association Meetings, Colby College, Federal Reserve Bank of Chicago, Miami University, Notre Dame Macro Seminar, Sam Houston State University, University of Colorado, University of New Hampshire, University of Mississippi, and 2015 WAMS Sydney. We thank Tom Cosimano and Alex Maynard for comments on an earlier draft dated March 2015. All errors are our own.

# Introduction

In this paper, we study the cross-section of carry-trade generated currency excess returns in terms of their exposure to risk. We focus attention on global risk factors, constructed from macroeconomic fundamentals. The factors are designed to reflect variations in global macroeconomic uncertainty. These risk factors are high-minus low (HML) differences in conditional moments of macroeconomic performance indicators between the top and bottom quartiles of countries. These HML conditional moment measures are an enhancement over standard measures of uncertainty because they allow asymmetries in the distribution of the global state to be revealed.

We show that the HML skewness of the unemployment gap is a global fundamental risk factor that is priced in currency excess returns. The factor is constructed by computing the conditional skewness of each country's unemployment gap and subtracting the average value in the bottom quartile from the average in the top quartile. Countries in the high component have a large probability of above normal unemployment. They have a higher than normal chance of entering the bad state. Countries in the low component, which is typically negative, have a large probability of below normal unemployment. These countries have a higher than normal chance of entering the good state. The empirical factor, while a bit unconventional, captures variation in divergence, disparity, and inequality of fortunes across national economies, which we view as variations in global uncertainty. We show that this factor is robust to alternative conditional moments (mean and volatility) and alternative macro fundamentals (changes in the unemployment rate, output gap, output growth, real exchange rate gap, real exchange rate depreciation, consumption growth rate, and inflation rate).

A legacy literature has sought to understand currency excess returns by trying to resolve the forward premium anomaly–recognized as an empirical regularity since Hansen and Hodrick (1980), Bilson (1981), and Fama (1984). That is, in regressions of the future exchange rate depreciation on the interest rate differential, the slope coefficient is not equal to one as implied by the zero-profit uncovered interest rate parity (UIP) condition, but is typically negative. Because the interest rate differential between the two countries is not fully offset by subsequent exchange rate movements, systematically positive excess returns can be generated by shorting the low interest rate country's currency and using the proceeds to take a long position in the high interest rate country's currency. Hodrick (1987), Engel (1996) and Lewis (1996) survey earlier work on the topic, which viewed excess returns as risk premia and emphasized the time-series properties of individual currency excess returns. Whether through estimation or quantitative evaluation of asset pricing models, explanatory power was low and this body of work was unable to produce or identify mechanisms for risk-premia that were sufficiently large or acceptably correlated with the excess returns.[1]

The forward premium anomaly implies non-zero currency excess returns, but these are two different and distinct phenomena (see Hassan and Mano (2014)). In our data, there is no forward premium anomaly associated with the most profitable carry trade excess returns. Recent research in international finance de-emphasizes the forward premium anomaly, focuses directly on currency excess returns and

[1]This is not to say interest in the topic has waned. See, for example, Alvarez et al. (2009), Bansal and Shaliastovich (2012), Chinn and Zhang (2015), Engel (2015), and Verdelhan (2010).

has produced new insights into their behavior. An important methodological innovation, introduced by Lustig and Verdelhan (2007), was to change the observational unit from individual returns to portfolios of returns. Identification of systematic risk in currency excess returns has long posed a challenge to this research and the use of portfolios aids in this identification by averaging out idiosyncratic return fluctuations. Since the returns are available to global investors, and portfolio formation allows diversification of country-specific risk, presumably only global risk factors remain to drive portfolio returns.

Following the literature, we study the macroeconomic determinants of excess returns implied by the carry trade.[2] The carry is a trading strategy where investors short portfolios of low-interest rate currencies and go long portfolios of high-interest rate currencies (e.g., Lustig and Verdelhan (2007, 2011), Burnside et al. (2011), Jorda and Taylor (2012), Clarida et al. (2009), Christiansen et al. (2011)). Estimation follows the 'two-pass' procedure used in finance. In the first pass, portfolio excess returns are regressed on the macro risk factors in a time-series regression to obtain the betas. In the second pass, using a single cross-sectional regression, mean excess returns are regressed on the betas to estimate factor risk premium. Inference is drawn using generalized method of moments standard errors, as presented in Cochrane (2005), which take into account that the betas in the second stage are not data but are generated regressors.

We then draw on an affine yield model of the term structure of interest rates, adapted to pricing currency excess returns, to interpret and provide context for the empirical results. The model is closely related to Lustig et al. (2011), Brennan and Xia (2006) and Backus et al. (2001), who consider various extensions of Cox et al. (1985). In the model, countries' log stochastic discount factors (SDFs) exhibit heterogeneity in the way they load on a country-specific factor and a common global risk factor (the HML skewness in the unemployment gap). We estimate the model parameters using simulated method of moments (Lee and Ingram (1991)) and show that the model can qualitative replicate key features of the data.

Our paper is related to, but contrasts with relative asset pricing research of Lustig et al. (2011), Daniel et al. (2014), and Ang and Chen (2010), for example, who study the pricing of risk factors built from asset returns in currency excess returns. Our paper falls in the class of absolute asset pricing research in that our primary interest is in understanding the macroeconomic basis of risk in currency excess returns. This paper is more closely related related Lustig and Verdelhan (2007), Burnside et al. (2011), and Menkhoff et al. (2013), who also model global risk factors with macroeconomic data.[3] Our paper also makes contact with papers that study the role of higher-ordered moments. Menkhoff et al. (2012) find a relation between carry excess returns and global foreign exchange rate volatility, and

[2]Alternatively, Menkhoff et al. (2013), for example, find profitable currency excess returns can be generated by sorting on first moments of variables associated with the monetary approach to exchange rate determination. This paper only studies carry trade generated excess returns.

[3]Other recent contributions, using alternative approaches, include Burnside et al.'s (2011) peso problem explanation, Bansal and Shalistovich's (2012) and Colacito and Croce's (2011) long-run risk models, and Verdelhan's (2010) habit persistence model. Also, Ready et al. (2015) who explain currency excess returns by trade and production patterns and Hassan (2013) who focuses on country size.

Brunnermeier et al. (2009) investigate the relationship between carry excess returns and skewness of exchange rate changes.

The remainder of the paper is organized as follows. The next section discusses the construction of portfolios of currency excess returns. Section 2 describes the data. Section 3 implements the main empirical work. Section 4 provides a further examination of the global risk factor. Section 5 presents the affine asset pricing model, and Section 6 concludes.

# 1 Portfolios of Currency Excess Returns

Identification of systematic risk in currency returns has long posed a challenge in international finance. In early research on single-factor models (e.g., Frankel and Engel (1984), Cumby (1988), Mark (1988)), the observational unit was the excess U.S. dollar return against a single currency. Lustig and Verdelhan (2007) innovated on the methodology by working with portfolios of currency excess returns instead of returns for individual currencies. This is a useful way to organize the data because it averages out noisy idiosyncratic and non-systematic variation and improves the ability to uncover systematic risk. Global investors, who have access to these returns, can diversify away country specific risk. As a result, in a world of integrated financial markets, only undiversifiable global risk factors will be priced.

Before forming portfolios, we start with the bilateral carry trade. Let there be $n_t + 1$ currencies available at time $t$. Let the nominal interest rate of country $i$ be $r_{i,t}$ for $i = 1, ..., n_t$, and the U.S. nominal interest rate be $r_{0,t}$. The U.S. will always be country '0.' In the carry, we short the U.S. dollar (USD) and go long currency $i$ if $r_{i,t} > r_{0,t}$. The expected bilateral excess return is

$$E_t \left( (1 + r_{i,t}) \frac{S_{i,t+1}}{S_{i,t}} - (1 + r_{0,t}) \right) \simeq E_t \left( \Delta \ln \left( S_{i,t+1} \right) \right) + r_{i,t} - r_{0,t}, \tag{1}$$

where $S_{i,t}$ is the USD price of currency $i$ (an increase in $S_{i,t}$ means the USD depreciates relative to currency $i$). If $r_{0,t} > r_{i,t}$, short currency $i$ and go long the USD.

Next, extend the carry trade to a multilateral setting. Rank countries by interest rates from low to high in each time period, and use this ranking to form portfolios of currency excess returns. As in Lustig et al. (2011), we form six such portfolios. Call them $P_1, \ldots, P_6$. The portfolios are rebalanced every period. Portfolios are arranged from low ($P_1$) to high ($P_6$) where $P_6$ is the equally weighted average return from those countries in the highest quantile of interest rates and $P_1$ is the equally weighted average return from the lowest quantile of interest rates. Excess portfolio returns are stated relative to the U.S.,

$$\frac{1}{n_{j,t}} \sum_{i \in P_j} (1 + r_{i,t}) \frac{S_{i,t+1}}{S_{i,t}} - (1 + r_{0,t}), \tag{2}$$

for $j = 1, \ldots, 6$. In this approach, the exchange rate components of the excess returns are relative to the USD. The USD is the funding currency if the average of $P_j$ interest rates are higher than the U.S. rate and vice-versa. An alternative, but equivalent approach would be to short any of the $n_t + 1$ currencies and to go long in the remaining $n_t$ currencies. Excess returns would be constructed by 'differencing' the portfolio return, as in Lustig et al. (2013) and Menkhoff et al. (2013), by subtracting the $P_1$ return from $P_2$ through $P_6$.[4] It does not matter, however, whether excess returns are formed by the 'difference' method or by subtracting the U.S. interest rate. As Burnside (2011a) points out, portfolios formed by one method are linear combinations of portfolios formed by the other. The next section describes the data we use to construct the portfolios of currency excess returns as well as some properties of the excess return data.

# 2 The Data

The raw data are quarterly and have a maximal span from 1973Q1 to 2014Q2. When available, observations are end-of-quarter and point sampled. Cross-country data availability varies by quarter. At the beginning of the sample, observations are available for 10 countries. The sample expands to include additional countries as their data become available, and contracts when data vanishes (as when countries join the Euro). Our encompassing sample is for 41 countries plus the Euro area. The countries are Australia, Austria, Belgium, Brazil, Canada, Chile, Colombia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Romania, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, and the United States. Countries that adopt the Euro are dropped when they join the common currency. The data set consists of exchange rates, interest rates, consumption, gross domestic product (GDP), unemployment rates, and the consumer price index (CPI). Details are elaborated below.

The data are *not* seasonally adjusted. Census seasonal adjustment procedures impound future information into today's seasonally adjusted observations, which is generally unwelcome. We remove the seasonality ourselves with a moving average of the current and three previous quarters of the variable in question.

The exchange rate, $S_{j,t}$, is expressed as USD per foreign currency units so that a higher exchange rate represents an *appreciation* of the *foreign* currency relative to the USD. In the early part of the sample, exchange rates and interest rates for Australia, Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Switzerland, United Kingdom, and the United States are from the Harris Bank *Weekly Review*. These are last Friday of the quarter quotations from 1973Q1 to 1996Q1. All other exchange rate observations are from Bloomberg.

One consideration in forming our sample of countries was based on availability of rates on interbank or Eurocurrency loans, which are assets for which traders can take short positions. Because these rates for alternative currencies are often quoted by the same bank, Eurocurrency/interbank rates net out cross-country differences in default risk. From 1973Q1 to 1996Q1, interest rates are 3-month Eurocurrency rates. All other interest rate observations are from *Datastream*. When available, the

[4] If there are $n_{j,t}$ currencies (excluding the reference currency) in portfolio $P_j$, the USD ex post $P_6 - P_1$ excess return is

$$\frac{1}{n_{6,t}} \sum_{i \in P_6} (1 + r_{i,t}) \frac{S_{i,t+1}}{S_{i,t}} - \frac{1}{n_{1,t}} \sum_{k \in P_1} (1 + r_{k,t}) \frac{S_{k,t+1}}{S_{k,t}}. \tag{3}$$

interest rates are 3-month interbank rates. In a handful of cases, interbank rates are not available so we imputed rates from spot and forward exchange rates. Interest rates can be imputed from the foreign exchange forward premium since covered interest parity holds except in rare instances of crisis and market turmoil. We preferred to use interbank rates when available, however, because the imputed interest rates were found to be excessively volatile and were often negative (in periods before central banks began paying negative interest). Additional details on interest rate sampling are provided in the appendix.

Real consumption and GDP are from Haver Analytics. The unemployment rate and the consumer price index ($P_{j,t}$) are from the FRED database at the Federal Reserve Bank of St. Louis. The log real exchange rate between the U.S (country '0') and country $j$ is $q_{j,t} \equiv \ln\left(\left(S_{j,t}P_{j,t}\right)/P_{0,t}\right)$.

In many cases, due to the relatively short time-span of the data, the real exchange rate and unemployment rate observations appear to be non-stationary. To induce stationarity in these variables, we work with their 'gap' versions. The gap variables are cyclical components from a recursively applied Hodrick-Prescott (1997) (HP) filter. The HP filter is applied recursively so as not to introduce future information into current observations. The GDP gap is constructed similarly.

In the next subsection, we construct portfolios of currency excess returns using the raw data described above and outline some key properties of this data.

## 2.1 Some properties of the data

We follow Lustig et al. (2011) and sort countries by the interest rate in each time period into six equally-weighted carry-trade portfolios. The U.S. interest rate is subtracted from each portfolio return to form excess returns which are stated in percent per annum.

Table 1: Carry (Excess) Return Summary Statistics, 1978Q1-2014Q2

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ |
|---|---|---|---|---|---|---|
| Mean Excess | -0.421 | 0.605 | 1.729 | 2.194 | 3.241 | 8.194 |
| Sharpe Ratio | -0.023 | 0.034 | 0.101 | 0.114 | 0.175 | 0.348 |
| Mean Return | 5.430 | 6.457 | 7.580 | 8.046 | 9.093 | 14.046 |
| Sharpe Ratio | 0.302 | 0.375 | 0.468 | 0.435 | 0.492 | 0.623 |

Table 1 shows the portfolio mean excess returns, the mean returns and their Sharpe ratios over the full sample 1978Q1–2014Q2. Both the mean excess returns and the mean returns increase monotonically across the portfolios. There is not much variation in average excess returns and average returns between $P_4$ and $P_5$. There is a sizable jump in the average return and excess return from $P_5$ to $P_6$. These six portfolios will be the cross-section of returns that we analyze below.[5]

Figure 1 plots the cumulated excess returns from shorting the dollar and going long the foreign currency portfolios. The carry trade performs poorly before the mid 1980s, but its profitability takes

[5]While the data begin 1973Q1, we lose 20 startup observations in constructing the risk factors.

off around 1985. The observations available in the 1970s are mostly European countries, who held a loose peg against the deutschemark, initially through the 'Snake in the Tunnel,' and then in 1979 through the European Monetary System. During this period, there is not much cross-sectional variety across countries, especially in their exchange rate movements against the dollar. The U.S. nominal interest rate was also relatively high during this time period.

Figure 1: Cumulated Excess Returns on Six Carry Portfolios

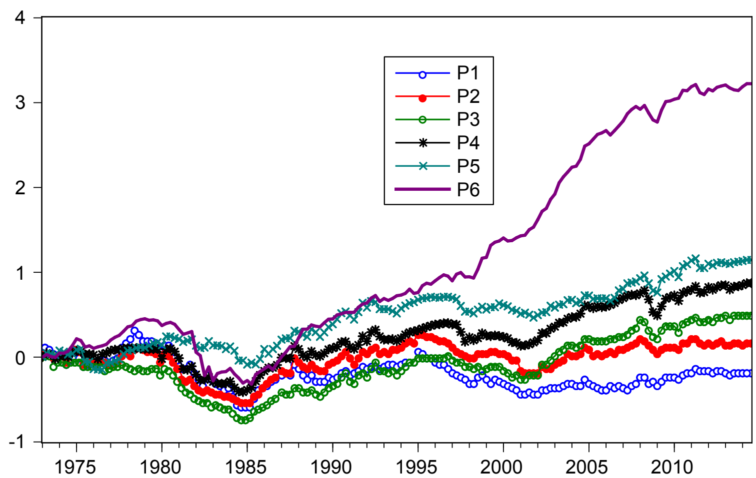
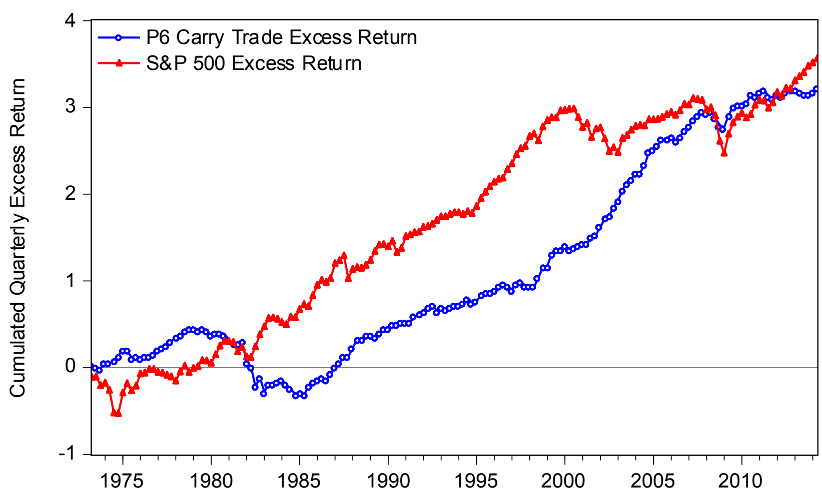



Figure 2: Cumulated Excess Returns on $P_6$ Carry Portfolio and the Standard and Poors 500



For additional context, Figure 2 plots the cumulated $P_6$ excess return along with the cumulated excess return on the Standard and Poors 500 index over the same time-span. The $P_6$ excess return is first-order large and important.

Table 2: Decomposition of Carry Excess Returns (Log Approximation), 1978Q1-2014Q2

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ |
|---|---|---|---|---|---|---|
| Carry excess return | -1.161 | -0.367 | 0.645 | 1.317 | 1.936 | 6.941 |
| Interest rate differential | -2.916 | -1.055 | 0.669 | 2.326 | 4.871 | 16.464 |
| USD exchange rate depreciation | 1.755 | 0.688 | -0.024 | -1.008 | -2.934 | -9.523 |

Notes: USD exchange rate depreciation, $\Delta s_{t+1}$, is positive when the dollar falls in value.

Table 2 decomposes the portfolio excess returns into contributions from the interest rate differential and the exchange rate components. Interestingly, on average, there is no forward premium anomaly in the portfolio excess returns. To read the table, the average U.S. interest rate is 2.9% higher than the average $P_1$ interest rate. The average exchange rate return goes in the direction of uncovered interest rate parity (UIP), which predicts an average dollar depreciation of 2.9%. The actual average dollar depreciation is 1.8% against $P_1$ currencies. Similarly, the average $P_6$ interest rate is 16.5% higher than the average U.S. interest rate. UIP predicts an average dollar appreciation of 16.5% and the dollar actually appreciates 9.5% against $P_6$ currencies, on average. If the forward premium anomaly were present, the dollar would have depreciated. Figure 3 plots the relationship between the portfolio interest rate differential and the dollar depreciation. The relationships between the average interest rate differential and the average depreciation is consistent with Chinn and Merideth's (2004) findings of long-horizon UIP.

Figure 3: Decomposition of Carry Excess Returns (Log Approximation)

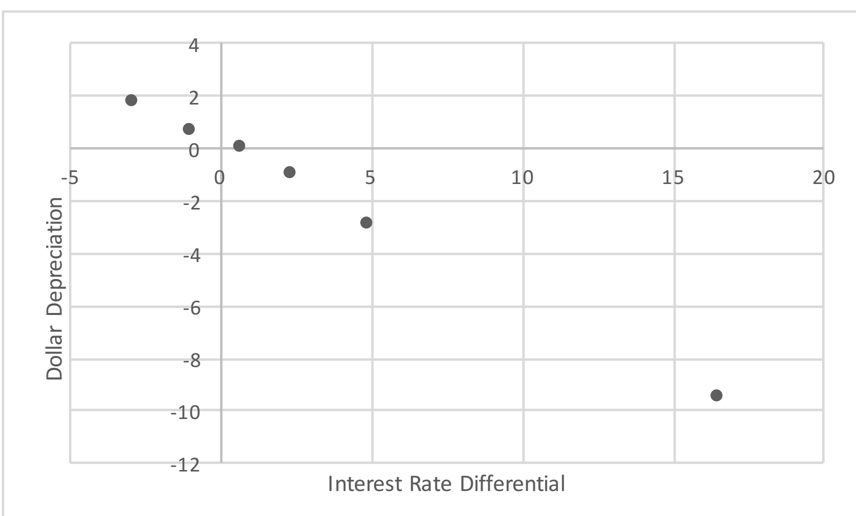


Table 3: Fama Regressions (Log Approximation), 1978Q1-2014Q2

| Dependent Variable | Regressor | Slope | t-ratio ($\beta=0$) | t-ratio ($\beta=1$) |
|---|---|---|---|---|
| $\Delta s_{t+1}^{P_6}$ | $r_{0,t}-r_t^{P_6}$ | 0.580 | 3.328 | -2.407 |
| $\Delta s_{t+1}^{P_5}$ | $r_{0,t}-r_t^{P_5}$ | 1.302 | 2.174 | 0.504 |
| $\Delta s_{t+1}^{P_4}$ | $r_{0,t}-r_t^{P_4}$ | 0.251 | 0.353 | -1.057 |
| $\Delta s_{t+1}^{P_3}$ | $r_{0,t}-r_t^{P_3}$ | -0.942 | -1.387 | -2.859 |
| $\Delta s_{t+1}^{P_2}$ | $r_{0,t}-r_t^{P_2}$ | -0.424 | -0.675 | -2.268 |
| $\Delta s_{t+1}^{P_1}$ | $r_{0,t}-r_t^{P_1}$ | -0.561 | -1.134 | -3.153 |

What about the short-run relationship between interest rates and exchange rate returns? Table 3 reports estimates of the Fama (1984) regression for the six portfolios. Here, we regress the one-period ahead dollar depreciation of the $P_j$ portfolio ($j=1,...,6$) on the U.S. – $P_j$ interest differential. Let $\Delta s_{t+1}^{P_j} \equiv \frac{1}{n_{j,t}} \sum_{i \in P_j} \ln\left(\frac{S_{j,t+1}}{S_{j,t}}\right)$ be the dollar depreciation against portfolio $j$ and $r_t^{P_j} \equiv \frac{1}{n_{j,t}} \sum_{i \in P_j} r_{j,t}$ be portfolio $j's$ average yield. The Fama regression we run is,

$$\Delta s_{t+1}^{P_j} = \alpha_j + \beta_{F,j}\left(r_{0,t} - r_t^{P_j}\right) + \epsilon_{j,t+1}.$$

According to the point estimates, there is a forward premium anomaly for $P_1$, $P_2$, and $P_3$. Those are portfolios whose interest rates are relatively close to U.S. interest rates. There is no forward premium anomaly for portfolios with large interest rate differentials relative to the United States. In particular, the slope for $P_5$ exceeds 1. Currencies of countries whose interest rates are systematically high relative to the U.S. tend to depreciate in accordance with UIP.

The results in Tables 1, 2, and 3 illustrate how in our data set, as emphasized in Hassan and Mano (2014), currency excess returns and the forward premium anomaly are different and distinct phenomena. We find no forward premium anomaly in the portfolios that earn the largest excess returns. We do find a forward premium anomaly associated with the portfolios that earn the smallest excess returns.

Conceptually, the distinction between the forward premium anomaly and currency excess returns can be seen as follows. Let $M_{j,t}$ be the *nominal* stochastic discount factor (SDF) for country $j$. The investors' Euler equations for pricing nominal bonds gives $r_{0,t} - r_{j,t} = \ln(E_t M_{j,t+1}) - \ln(E_t M_{0,t+1})$. In a complete markets environment (or an incomplete markets setting with no arbitrage), the stochastic discount factor approach to the exchange rate (Lustig and Verdelhan (2012)) gives $\Delta \ln(S_{j,t+1}) = \ln(M_{j,t+1}) - \ln(M_{0,t+1})$. The forward premium anomaly is a story about the negative covariance,

$$\mathrm{Cov}_t\left(\Delta \ln(S_{j,t+1}), r_{0,t} - r_{j,t}\right) = \mathrm{Cov}_t\left(\ln\left(\frac{M_{j,t+1}}{M_{0,t+1}}\right), \ln\left(\frac{E_t M_{j,t+1}}{E_t M_{0,t+1}}\right)\right),$$

between relative log SDFs and relative log conditional expectations of SDFs.

The expected currency excess return, on the other hand, is a story about relative conditional variances of the log SDFs.[6] Following from the investors' Euler equations, $E_t\left(\Delta \ln(S_{j,t+1}) + r_{j,t} - r_{0,t}\right) =$

[6] If the log SDF is not normally distributed, Backus, Foresi and Telmer (2001) show that the expected currency excess return depends on a series of higher ordered cumulants of the log SDFs.

$\ln\left(\frac{E_t M_{0,t+1}}{E_t M_{j,t+1}}\right) - \left[E_t\left(\ln\left(M_{0,t+1}\right)\right) - E_t\left(\ln\left(M_{j,t+1}\right)\right)\right]$. If the stochastic discount factors are log-normally distributed, the expected currency excess return simplifies to the difference in the conditional variance of the log SDFs,

$$E_t\left(\Delta \ln\left(S_{j,t+1}\right) + r_{j,t} - r_{0,t}\right) = \frac{1}{2}\left(\mathrm{Var}_t\left(\ln\left(M_{0,t+1}\right)\right) - \mathrm{Var}_t\left(\ln\left(M_{j,t+1}\right)\right)\right). \tag{4}$$

According to equation (4), country $j$ is 'risky' and pays a currency premium if its log SDF is less volatile than country '0' (U.S.). When country $j$ residents live in relative stability, the need for precautionary saving is low. Hence, bond prices in country $j$ will be relatively low. The relatively high returns this implies contributes to a higher currency excess return.

In the remainder of the paper we de-emphasize the forward premium anomaly and focus directly on currency excess returns.

# 3 Global Macro Fundamental Risk in Currency Excess Returns

This section addresses the central issue of the paper. Does the cross-section of carry-trade generated currency excess returns vary according to their exposure to macro-fundamentals based risk factors? Burnside et al. (2011) found little evidence that any macro-variables were priced. Lustig and Verdelhan's (2007) analysis of U.S. consumption growth as a risk factor was challenged by Burnside (2011). Menkhoff et al. (2012) price carry trade portfolios augmented by portfolios formed by ranking variables used in the monetary approach to exchange rates. Our view is that the explanatory power of existing studies remains unsettled.

Our notion is global macroeconomic risk is high in times of high divergence, disparity or inequality in economic performance across countries. We characterize the divergence in economic performance with high-minus-low (HML) conditional moments of country standard macroeconomic fundamentals. We consider eight macro variables. These include,

1. Unemployment rate gap, $UE^{gap}$
2. Change in unemployment rate, $\Delta UE$
3. GDP growth, $\Delta y$
4. GDP gap, $y^{gap}$
5. Real exchange rate gap, $q^{gap}$
6. Real exchange rate depreciation, $\Delta q$
7. Aggregate consumption growth, $\Delta c$
8. Inflation rate, $\pi$

The rationale for unemployment, consumption growth and GDP measures should be obvious. Inflation, especially at higher levels, is associated with the economic state by depressing economic activity. We try to obtain information on the international distribution of log SDFs through consideration of the real exchange rate gap. By the SDF approach to exchange rates (Lustig and Verdelhan (2012)), the real depreciation is the foreign-U.S. difference in log real SDFs, $\Delta q_{i,t} = n_{i,t} - n_{0,t}$. Real exchange rates are relative to the United States. Both gap and rates of change are employed to induce stationarity in the real exchange rate, unemployment rate, and GDP observations.

For each country, we compute time-varying (conditional) skewness $sk_t(\bullet)$, volatilities $\sigma_t(\bullet)$, and means $\mu_t(\bullet)$ of the eight variables. We approximate the conditional moments with sample moments computed from a backward-looking moving 20-quarter window.[7] We then form HML versions of these variables by subtracting the average value in the bottom quartile from the average in the top quartile.

Increasing HML conditional mean variables signify greater inequality across countries in various measures of growth. We include volatility as it is a popular measure of uncertainty. Increasing HML conditional volatility signifies greater disparities in macroeconomic uncertainty across countries. The HML conditional skewness measure provides an alternative and asymmetric measure of macroeconomic uncertainty. High (low) skewness means a high probability of a right (left) tail event.

## 3.1 Estimation

We employ the two-pass regression method used in finance to estimate how the cross-section of carry trade excess returns are priced by the HML macroeconomic risk factors described above. Inference is drawn using generalized method of moments (GMM) standard errors described in Cochrane (2005).

*Two-pass regressions.* Let $\left\{r^e_{i,t}\right\}$, $i = 1, ...N, t = 1, ..., T$, be our collection of $N = 6$ carry trade excess returns. Let $\left\{f^{HML}_{k,t}\right\}$, $k = 1, .., K$, be the collection of potential HML macro risk factors. In the first pass, we run $N = 6$ individual time-series regressions of the excess returns on the $K$ factors to estimate the factor 'betas' (the slope coefficients on the risk factors),

$$r^e_{i,t} = a_i + \sum_{k=1}^{K} \beta_{i,k} f^{HML}_{k,t} + \epsilon_{i,t}. \tag{5}$$

Covariance is risk, and the betas measure the extent to which the excess return is exposed to, or covaries with, the $k-th$ risk factor (holding everything else constant). If this risk is systematic and undiversifiable, investors should be compensated for bearing it. The risk should explain why some excess returns are high while others are low. This implication is tested in the second pass, which is the single cross-sectional regression of the (time-series) mean excess returns on the estimated betas,

$$\bar{r}^e_i = \gamma + \sum_{k=1}^{K} \lambda_k \beta_{i,k} + \alpha_i. \tag{6}$$

[7] We also considered using a 16-quarter and a 24-quarter window. The results are robust to these alternative window lengths. These results are reported in the appendix.

where $\bar{r}_i^e = (1/T)\sum_{t=1}^{T} r_{it}^e$ and the slope coefficient $\lambda_k$ is the risk premia associated with the $k-th$ risk factor.

In other contexts, the excess return is constructed relative to what the investor considers to be the risk-free interest rate. If the model is properly specified, the intercept $\gamma$, should be zero. In the current setting, the carry trades are available to global investors. When the trade matures, the payoff needs to be repatriated to the investor's home currency which entails some foreign exchange risk. Hence, the excess returns we consider are not necessarily relative to 'the' risk-free rate, and there is no presumption that the intercept $\gamma$, is zero.

To draw inference about the $\lambda's$, we recognize that the betas in equation (6) are not data, but are themselves estimated from the data. To do this, we compute the GMM standard errors, described in Cochrane (2005) and Burnside (2011b), that account for the generated regressors problem and for heteroskedasticity in the errors. Cochrane (2005) sets up a GMM estimation problem using a constant as the instrument, which produces the identical point estimates for $\beta_{i,k}$ and $\lambda_k$ as in the two-pass regression. The GMM procedure automatically takes into account that the $\beta_{i,k}$ are not data, per se, but are estimated and are functions of the data. It also is robust to heteroskedasticity and autocorrelation in the errors. Also available, is the covariance matrix of the residuals $\alpha_i$, which we use to test that they are jointly zero. The $\alpha_i$ are referred to as the 'pricing errors,' and should be zero if the model adequately describes the data. We get our point estimates by doing the two-pass regressions with least squares and get the standard errors by 'plugging in' the point estimates into the GMM formulae. Additional details are given in the appendix.

## 3.2 Empirical Results

We begin by estimating a one-factor model with the two-pass procedure where the single factor is one of the HML global macro risk factors discussed above. The sample starts in 1973Q1 but uses 20 startup observations to compute the conditional moments. Hence, betas and average returns are computed over the time span 1978Q1 to 2014Q2. Table 4 shows the the second stage estimation results for the single-factor model. In the first row, we see that the HML unemployment gap skewness factor is priced in the excess returns. The price of risk $\lambda$ is positive, the t-ratio is significant, the $R^2$ is very high and the constant $\gamma$ is not significant.

Several other factor candidates also appear to be priced, such as two other HML conditional skewness measures ($sk_t\,(\Delta UE)$ and $sk_t\,(\Delta y)$) and HML conditional volatilities and conditional means of $UE^{gap}$, $\Delta y$, $\Delta c$, and $\pi$. For these factor candidates, the t-ratios on $\lambda$ estimates are significant, the estimated intercepts $\gamma$ are insignificant, and many of the $R^2$ values are also quite high. However, it is not the case that generically forming HML specifications on conditional moments of macro fundamentals automatically get priced. The HML conditional volatilities of unemployment rate changes and the real exchange rate gap are not priced and these specifications have $R^2$ values near zero.

Eyeballing the single-factor results gives the informal impression that the HML $sk_t\,(UE^{gap})$ factor has an edge over alternative measures of the global risk factor. The price of risk has the highest t-ratio and the regression has the highest $R^2$. Figure 4 displays the scatter plot of the average portfolio currency

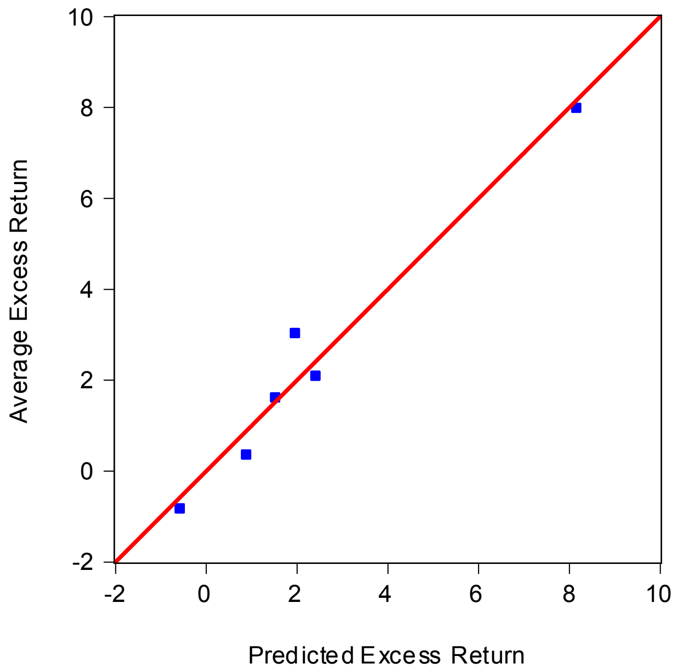
Table 4: Two-Pass Estimation of the Single-Factor Beta-Risk Model on Carry Excess Returns, 1978Q1-2014Q2

| Single-Factor Model. | | | | | | | |
|---|---|---|---|---|---|---|---|
| HML Factor | $\lambda$ | t-ratio | $\gamma$ | t-ratio | $R^2$ | Test-stat | p-val. |
| $sk_t(UE^{gap})$ | 0.485 | **3.532** | 1.798 | 0.904 | 0.965 | 1.498 | 0.913 |
| $sk_t(\Delta UE)$ | 0.743 | **2.508** | 2.269 | 0.767 | 0.939 | 1.458 | 0.918 |
| $sk_t(y^{gap})$ | 0.643 | 1.379 | 5.344 | 1.078 | 0.728 | 3.400 | 0.639 |
| $sk_t(\Delta y)$ | 0.410 | **2.364** | 3.931 | 1.633 | 0.323 | 7.141 | 0.210 |
| $sk_t(q^{gap})$ | 0.439 | 1.484 | 4.070 | 1.672* | 0.065 | 8.178 | 0.147 |
| $sk_t(\Delta q)$ | 1.308 | 1.755* | 6.401 | 1.728* | 0.593 | 3.319 | 0.651 |
| $sk_t(\Delta c)$ | 0.287 | 1.618 | 1.499 | 0.575 | 0.433 | 7.178 | 0.208 |
| $sk_t(\pi)$ | 0.365 | 1.224 | -3.960 | -0.839 | 0.186 | 4.824 | 0.438 |
| $\sigma_t(UE^{gap})$ | 2.804 | **2.302** | 3.124 | 1.173 | 0.436 | 7.004 | 0.220 |
| $\sigma_t(\Delta UE)$ | 0.025 | 0.687 | 1.873 | 1.150 | 0.016 | 10.266 | 0.068 |
| $\sigma_t(y^{gap})$ | 0.763 | **2.370** | 0.021 | 0.007 | 0.823 | 3.776 | 0.582 |
| $\sigma_t(\Delta y)$ | 1.359 | **2.291** | -0.900 | -0.376 | 0.731 | 4.925 | 0.425 |
| $\sigma_t(q^{gap})$ | 2.862 | 0.973 | -1.295 | -0.397 | 0.175 | 5.809 | 0.325 |
| $\sigma_t(\Delta q)$ | 15.104 | 1.741* | 7.269 | 1.247 | 0.865 | 1.847 | 0.870 |
| $\sigma_t(\Delta c)$ | 1.646 | **2.396** | -2.436 | -0.733 | 0.871 | 3.257 | 0.660 |
| $\sigma_t(\pi)$ | 2.454 | **2.252** | -0.183 | -0.088 | 0.549 | 7.902 | 0.162 |
| $\mu_t(UE^{gap})$ | 2.906 | **2.044** | 1.326 | 0.409 | 0.842 | 5.859 | 0.320 |
| $\mu_t(\Delta UE)$ | 0.071 | **2.035** | -0.426 | -0.153 | 0.593 | 7.967 | 0.158 |
| $\mu_t(y^{gap})$ | 0.599 | 1.941* | 0.793 | 0.297 | 0.703 | 6.460 | 0.264 |
| $\mu_t(\Delta y)$ | -1.522 | **-2.334** | 4.744 | **1.993** | 0.232 | 6.718 | 0.242 |
| $\mu_t(q^{gap})$ | 1.849 | **2.392** | 3.192 | 0.897 | 0.334 | 3.782 | 0.581 |
| $\mu_t(\Delta q)$ | 2.361 | 1.916* | -1.002 | -0.394 | 0.381 | 6.896 | 0.228 |
| $\mu_t(\Delta c)$ | -1.741 | **-2.215** | 4.968 | 1.407 | 0.352 | 3.474 | 0.627 |
| $\mu_t(\pi)$ | 7.029 | **2.716** | 1.174 | 0.600 | 0.736 | 6.418 | 0.268 |

Notes: The raw data are quarterly (1973Q1 to 2014Q2) and when available are end-of-quarter and point sampled. 20 quarters startup to compute initial HML factors. Model estimated on returns from 1978Q1 to 2014Q2. $\Delta y$, $y^{gap}$, $\Delta c$, $\Delta UE$, $UE^{gap}$, $\pi$, $q^{gap}$, and $\Delta q$ represent the GDP growth rate, GDP gap, consumption growth rate, change in the unemployment rate, unemployment gap, inflation rate, real exchange rate gap, and real exchange rate depreciation, respectively. For each country (41 countries plus the Euro area) and each macroeconomic variable ($x$), we compute the 'conditional' mean ($\mu_t(x)$), volatility ($\sigma_t(x)$) and skewness ($sk_t(x)$) using a 20-quarter window. To form the portfolio returns, we sort by the nominal interest rate (carry) for each country from low to high. The rank ordering is divided into six portfolios, into which the currency returns are assigned. $P_6$ is the portfolio of returns associated with the highest nominal interest rate countries and $P_1$ is the portfolio of returns associated with the lowest nominal interest rate countries. This table reports the two-pass procedure estimation results from a one-factor model. In the first pass, we run $N = 6$ individual time-series regressions of the excess returns on the $K$ factors to estimate the factor 'betas,' $r^e_{i,t} = a_i + \sum_{k=1}^{K} \beta_{i,k} f^{HML}_{k,t} + \epsilon_{i,t}$, where $r^e_{i,t}$ is the excess return, $\beta_{i,k}$ is the factor beta and $f^{HML}_{k,t}$ is the high-minus-low (HML) macro risk factor. The factors considered include the high-minus-low (HML) values of the conditional mean, volatility, and skewness of $\Delta y$, $y^{gap}$, $\Delta c$, $\Delta UE$, $UE^{gap}$, $\pi$, $q^{gap}$, and $\Delta q$. Each HML value is equal to the average in the highest quartile minus the average in the lowest quartile. In the second pass, we run a single cross-sectional regression of the (time-series) mean excess returns on the estimated betas, $\bar{r}^e_i = \gamma + \sum_{k=1}^{K} \lambda_k \beta_{i,k} + \alpha_i$, where $\bar{r}^e_i$ is the average excess return, $\gamma$ is the intercept, $\lambda_k$ is the risk premia, and $\alpha_i$ is the pricing error. The table reports the price of risk ($\lambda$) and its associated t-ratio (using GMM standard errors), the estimated intercept ($\gamma$) and its associate t-ratio, $R^2$ and the Wald test on the pricing errors (Test-stat) and its associated p-value (p-val.). Bold indicates significance at the 5% level. '*' indicates significance at the 10% level.

excess returns against the predicted values from the HML unemployment gap skewness single-factor model. The variation in predicted returns follows entirely from the variation in the betas.

Figure 4: Actual and Predicted Average Excess Returns by HML Unemployment Gap Skewness Beta Model.




Notes: The raw data are quarterly (1973Q1 to 2014Q2) and when available are end-of-quarter and point sampled. For each country (41 countries plus the Euro area), we compute the 'conditional' unemployment gap skewness using a 20-quarter window. To form the portfolio returns, we sort by the nominal interest rate for each country from low to high. The rank ordering is divided into six categories, into which the currency returns are assigned. $P_6$ is the portfolio of returns associated with the highest interest rate quantile and $P_1$ is the portfolio of returns associated with the lowest interest rate quantile. The excess returns are the average of the USD returns in each category minus the U.S. nominal interest rate and are stated in percent per annum. The figure plots the actual versus the predicted average excess return.

To assess more formally, the impression that HML $sk_t(UE^{gap})$ dominates, we estimate a two-factor model with the HML $sk_t(UE^{gap})$ as the maintained (first) factor and each of the alternative factor constructions as the second factor. Table 5 shows the two-factor estimation results.

Here, the HML unemployment gap skewness factor is significant at the 5% level in every case while none of the alternative factor candidates are significantly priced as a second factor at the 5% level . We continue to find the constant and the Wald test on the pricing errors to be insignificant. These results suggest that the HML unemployment gap skewness factor is the global macro risk factor for carry trade excess returns.

Table 5: Two-Pass Estimation of Two-Factor Beta-Risk Model on Carry Excess Returns, 1978Q1-2014Q2

| Two-Factor Model. First HML Factor is $sk_t(UE^{gap})$. | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $\lambda_1$ | t-ratio | $2^{nd}$ HML Factor | $\lambda_2$ | t-ratio | $\gamma$ | t-ratio | $R^2$ | Test-stat | p-val. |
| 0.443 | **2.670** | $sk_t(\Delta UE)$ | 0.468 | 1.125 | 1.825 | 0.806 | 0.956 | 1.431 | 0.921 |
| 0.490 | **3.409** | $sk_t(y^{gap})$ | 0.191 | 0.655 | 1.627 | 0.547 | 0.966 | 1.214 | 0.943 |
| 0.482 | **3.651** | $sk_t(\Delta y)$ | 0.117 | 0.629 | 1.922 | 0.841 | 0.966 | 0.938 | 0.967 |
| 0.458 | **3.200** | $sk_t(q^{gap})$ | -0.131 | -0.310 | 1.521 | 0.536 | 0.960 | 1.427 | 0.921 |
| 0.467 | **2.865** | $sk_t(\Delta q)$ | 0.104 | 0.205 | 2.090 | 0.719 | 0.966 | 1.373 | 0.927 |
| 0.539 | **2.889** | $sk_t(\Delta c)$ | -0.031 | -0.192 | 1.948 | 0.962 | 0.977 | 1.317 | 0.933 |
| 0.540 | **3.603** | $sk_t(\pi)$ | -0.158 | -0.884 | 4.242 | 1.361 | 0.985 | 0.572 | 0.989 |
| 0.404 | **3.098** | $\sigma_t(UE^{gap})$ | -0.495 | -0.513 | 1.835 | 0.821 | 0.937 | 3.059 | 0.691 |
| 0.463 | **3.065** | $\sigma_t(\Delta UE)$ | -0.056 | -1.312 | 1.744 | 0.730 | 0.927 | 2.975 | 0.704 |
| 0.374 | **2.880** | $\sigma_t(y^{gap})$ | 0.283 | 1.130 | 1.551 | 0.717 | 0.948 | 1.503 | 0.913 |
| 0.523 | **2.724** | $\sigma_t(\Delta y)$ | 0.040 | 0.059 | 2.108 | 0.872 | 0.905 | 3.068 | 0.690 |
| 0.463 | **3.090** | $\sigma_t(q^{gap})$ | -1.626 | -1.050 | 2.840 | 0.968 | 0.916 | 3.207 | 0.668 |
| 0.339 | **2.921** | $\sigma_t(\Delta q)$ | 8.811 | 1.405 | 4.218 | 1.044 | 0.955 | 3.176 | 0.673 |
| 0.319 | **2.294** | $\sigma_t(\Delta c)$ | 0.809 | 1.482 | -0.211 | -0.084 | 0.913 | 1.924 | 0.860 |
| 0.441 | **3.176** | $\sigma_t(\pi)$ | 0.599 | 0.612 | 2.074 | 0.868 | 0.917 | 3.211 | 0.668 |
| 0.366 | **2.628** | $\mu_t(UE^{gap})$ | 0.828 | 0.723 | 1.817 | 0.840 | 0.938 | 2.005 | 0.848 |
| 0.446 | **2.986** | $\mu_t(\Delta UE)$ | -0.006 | -0.196 | 1.639 | 0.769 | 0.894 | 3.288 | 0.656 |
| 0.489 | **2.712** | $\mu_t(y^{gap})$ | 0.034 | 0.123 | 2.269 | 1.000 | 0.949 | 2.238 | 0.815 |
| 0.466 | **3.552** | $\mu_t(\Delta y)$ | -1.189 | -1.777* | 2.687 | 1.136 | 0.954 | 2.387 | 0.793 |
| 0.387 | **2.883** | $\mu_t(q^{gap})$ | -0.145 | -0.339 | 1.128 | 0.455 | 0.961 | 0.854 | 0.973 |
| 0.438 | **3.157** | $\mu_t(\Delta q)$ | -0.509 | -0.423 | 2.585 | 0.960 | 0.924 | 2.713 | 0.744 |
| 0.474 | **3.571** | $\mu_t(\Delta c)$ | -1.122 | -1.753* | 2.621 | 1.053 | 0.952 | 2.334 | 0.801 |
| 0.436 | **2.996** | $\mu_t(\pi)$ | 1.565 | 0.514 | 1.347 | 0.544 | 0.901 | 3.248 | 0.662 |

Notes: See notes to Table 4.

Since we are constrained to quarterly observations due to the availability of the macro variables, we do not have a surplus of time-series observations. Nevertheless, we can do some limited subsample analyses. So, we ask if our results are driven by the global financial crisis. Lustig and Verdelhan (2011) point to the poor performance of the carry trade during the crisis as an example of the risk born by international investors in the carry trade. To answer this question, we end the sample in 2008Q2. Table 6 shows the mean excess returns and Sharpe ratios for the interest rate sorted portfolios over this time span. Again, there is not much separation between $P_4$ and $P_5$ average excess returns, but there is a large spread between returns on $P_6$ and $P_1$.

Table 6: Pre-Crisis Carry Excess Return Summary Statistics, 1978Q1-2008Q2

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ |
|---|---|---|---|---|---|---|
| Mean Excess | -1.673 | -0.445 | 0.188 | 1.229 | 1.726 | 7.417 |
| Sharpe Ratio | -0.084 | -0.023 | 0.011 | 0.069 | 0.096 | 0.323 |

Table 7: Pre-Crisis Two-Pass Estimation of Single-Factor Beta-Risk Model on Carry Excess Returns, 1978Q1-2008Q2

| Single-Factor Model. | | | | | | | |
|---|---|---|---|---|---|---|---|
| HML Factor | $\lambda$ | t-ratio | $\gamma$ | t-ratio | $R^2$ | Test-stat | p-val. |
| $sk_t(UE^{gap})$ | 0.487 | **2.579** | 3.253 | 1.116 | 0.933 | 1.172 | 0.948 |
| $sk_t(\Delta UE)$ | 0.788 | **2.138** | 2.540 | 0.646 | 0.895 | 1.349 | 0.930 |
| $sk_t(y^{gap})$ | 0.674 | 1.055 | 4.734 | 0.726 | 0.847 | 0.804 | 0.977 |
| $sk_t(\Delta y)$ | 0.413 | **1.963** | 3.415 | 1.107 | 0.310 | 5.526 | 0.355 |
| $sk_t(q^{gap})$ | 0.863 | 1.601 | 5.974 | 1.245 | 0.315 | 3.507 | 0.622 |
| $sk_t(\Delta q)$ | 1.341 | 1.391 | 7.133 | 1.428 | 0.433 | 3.086 | 0.687 |
| $sk_t(\Delta c)$ | 0.292 | 1.363 | 0.485 | 0.148 | 0.495 | 5.694 | 0.337 |
| $sk_t(\pi)$ | 0.296 | 1.027 | -2.790 | -0.623 | 0.137 | 5.705 | 0.336 |
| $\sigma_t(UE^{gap})$ | 3.153 | **2.126** | 4.117 | 1.272 | 0.521 | 5.243 | 0.387 |
| $\sigma_t(\Delta UE)$ | 0.020 | 0.481 | 2.179 | 1.164 | 0.008 | 10.526 | 0.062 |
| $\sigma_t(y^{gap})$ | 0.817 | **2.013** | 0.884 | 0.236 | 0.785 | 3.878 | 0.567 |
| $\sigma_t(\Delta y)$ | 1.344 | **1.996** | -0.255 | -0.092 | 0.703 | 5.183 | 0.394 |
| $\sigma_t(q^{gap})$ | 3.009 | 1.002 | -2.197 | -0.527 | 0.288 | 4.215 | 0.519 |
| $\sigma_t(\Delta q)$ | 18.801 | 1.281 | 11.585 | 1.121 | 0.727 | 1.421 | 0.922 |
| $\sigma_t(\Delta c)$ | 1.196 | **2.661** | -0.772 | -0.248 | 0.837 | 2.842 | 0.724 |
| $\sigma_t(\pi)$ | 2.089 | 1.665* | -0.569 | -0.196 | 0.451 | 7.385 | 0.194 |
| $\mu_t(UE^{gap})$ | 3.198 | 1.792* | 1.234 | 0.292 | 0.858 | 4.489 | 0.481 |
| $\mu_t(\Delta UE)$ | 0.068 | 1.955* | -0.239 | -0.072 | 0.615 | 7.624 | 0.178 |
| $\mu_t(y^{gap})$ | 0.669 | 1.618 | 0.801 | 0.222 | 0.693 | 6.008 | 0.305 |
| $\mu_t(\Delta y)$ | -1.063 | -1.872* | 4.141 | 1.713* | 0.101 | 8.427 | 0.134 |
| $\mu_t(q^{gap})$ | 0.997 | **2.339** | 3.912 | 1.279 | 0.053 | 6.425 | 0.267 |
| $\mu_t(\Delta q)$ | 2.493 | 1.431 | -1.555 | -0.444 | 0.271 | 5.861 | 0.320 |
| $\mu_t(\Delta c)$ | -0.594 | -1.377 | 3.711 | 1.509 | 0.044 | 10.658 | 0.059 |
| $\mu_t(\pi)$ | 6.359 | 1.841* | 1.215 | 0.426 | 0.679 | 4.364 | 0.498 |

Notes: See notes to Table 4.

Table 7 shows the results from the single-factor estimation over the pre-crisis sample. The HML $sk_t\left(UE^{gap}\right)$ factor again gives the highest $R^2$ whereas the HML $\sigma_t\left(\Delta c\right)$ factor has a slightly higher t-ratio on the $\lambda$ estimate. Fewer of the alternative factor measures are significantly priced. This could be because they were more pronounced during the crisis or because we have a smaller sample having lost 24 quarterly observations–a reduction of 16 percent of the time-series observations.

Table 8: Pre-Crisis Two-Pass Estimation of Two-Factor Beta-Risk Model on Carry Excess Returns, 1978Q1-2008Q2

| | | Two-Factor Model. First HML Factor is $sk_t(UE^{gap})$. | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $2^{nd}$ HML | | | | | | | |
| $\lambda_1$ | t-ratio | Factor | $\lambda_2$ | t-ratio | $\gamma$ | t-ratio | $R^2$ | Test-stat | p-val. |
| 0.437 | **1.968** | $sk_t(\Delta UE)$ | 0.533 | 1.226 | 2.785 | 0.906 | 0.921 | 1.046 | 0.959 |
| 0.458 | **2.121** | $sk_t(y^{gap})$ | 0.285 | 0.457 | 3.494 | 0.879 | 0.935 | 0.844 | 0.974 |
| 0.478 | **2.878** | $sk_t(\Delta y)$ | 0.114 | 0.439 | 3.332 | 1.084 | 0.936 | 0.877 | 0.972 |
| 0.529 | **2.593** | $sk_t(q^{gap})$ | -0.194 | -0.279 | 2.567 | 0.519 | 0.941 | 1.085 | 0.955 |
| 0.453 | **2.313** | $sk_t(\Delta q)$ | 0.020 | 0.028 | 3.728 | 0.882 | 0.936 | 1.117 | 0.953 |
| 0.635 | **1.976** | $sk_t(\Delta c)$ | -0.130 | -0.450 | 4.523 | 1.439 | 0.971 | 0.552 | 0.990 |
| 0.540 | **2.519** | $sk_t(\pi)$ | -0.177 | -0.591 | 7.207 | 1.371 | 0.981 | 0.331 | 0.997 |
| 0.416 | **2.267** | $\sigma_t(UE^{gap})$ | -0.492 | -0.301 | 3.492 | 0.982 | 0.890 | 2.462 | 0.782 |
| 0.494 | **2.119** | $\sigma_t(\Delta UE)$ | -0.090 | -1.161 | 3.225 | 0.862 | 0.881 | 2.262 | 0.812 |
| 0.349 | **2.270** | $\sigma_t(y^{gap})$ | 0.396 | 1.129 | 3.100 | 0.993 | 0.892 | 2.304 | 0.806 |
| 0.468 | 1.932* | $\sigma_t(\Delta y)$ | 0.498 | 0.578 | 3.668 | 1.023 | 0.805 | 2.747 | 0.739 |
| 0.463 | **2.480** | $\sigma_t(q^{gap})$ | -1.351 | -0.745 | 4.771 | 1.256 | 0.827 | 2.540 | 0.770 |
| 0.329 | 1.905* | $\sigma_t(\Delta q)$ | 10.992 | 1.288 | 7.478 | 1.384 | 0.913 | 2.477 | 0.780 |
| 0.272 | 1.787* | $\sigma_t(\Delta c)$ | 1.054 | **2.406** | 0.135 | 0.041 | 0.843 | 2.316 | 0.804 |
| 0.489 | **2.188** | $\sigma_t(\pi)$ | -0.080 | -0.055 | 4.882 | 1.275 | 0.855 | 2.121 | 0.832 |
| 0.281 | 1.698* | $\mu_t(UE^{gap})$ | 1.540 | 1.208 | 2.758 | 0.785 | 0.900 | 2.859 | 0.722 |
| 0.405 | **2.241** | $\mu_t(\Delta UE)$ | 0.011 | 0.320 | 2.789 | 0.965 | 0.798 | 3.153 | 0.676 |
| 0.506 | **2.021** | $\mu_t(y^{gap})$ | -0.123 | -0.243 | 4.727 | 1.301 | 0.905 | 2.043 | 0.843 |
| 0.439 | **2.594** | $\mu_t(\Delta y)$ | -1.461 | -1.428 | 4.518 | 1.328 | 0.915 | 2.021 | 0.846 |
| 0.390 | **2.132** | $\mu_t(q^{gap})$ | -0.238 | -0.372 | 2.334 | 0.600 | 0.915 | 1.759 | 0.881 |
| 0.439 | **2.421** | $\mu_t(\Delta q)$ | -0.853 | -0.512 | 4.374 | 1.141 | 0.824 | 3.387 | 0.641 |
| 0.433 | **2.760** | $\mu_t(\Delta c)$ | -1.032 | -1.224 | 4.607 | 1.204 | 0.892 | 1.961 | 0.854 |
| 0.487 | 1.801* | $\mu_t(\pi)$ | -0.205 | -0.037 | 3.527 | 0.900 | 0.820 | 2.293 | 0.807 |

Notes: See notes to Table 4.

In Table 8 we evaluate robustness by maintaining HML $sk_t\,(UE^{gap})$ as the first factor and alternating the second factor. HML skewness in the unemployment gap remains significant at the 5% level in 18 specifications and at the 10% level in the remaining 5 specifications. The only alternative factor that is significantly priced is the HML conditional volatility of consumption growth.

In the foregoing analysis, we sorted countries into portfolios and found that their excess returns varied proportionately with their betas on the HML $sk_t\,(UE^{gap})$ factor. Additional evidence that this variable provides a risk-based explanation would be if the betas of individual excess returns vary and are increasing in those returns. To investigate along these lines, for each individual currency $i$, at time $t$, we create an excess return by going long (short) that currency if its interest rate is higher (lower) than the U.S. interest rate. We then estimate beta for each currency individually, and sort the excess returns into portfolios by their beta.

Table 9: Mean Carry Excess Returns, 1978Q1-2014Q2

| Six quantiles | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ |
|---|---|---|---|---|---|---|
| Mean Excess Return | 2.362 | 2.321 | 1.650 | 4.014 | 3.789 | 8.796 |
| Three quantiles | $P_1$ | $P_2$ | $P_3$ | | | |
| Mean Excess Return | 2.342 | 2.832 | 6.293 | | | |

Table 9 shows the average excess returns from sorting into six beta-ranked portfolios are low for low-beta portfolios and high for high beta portfolios. While they do not increase monotonically, average excess returns rise monotonically if we sort less finely into three quantiles instead of six.

There are both positive beta and negative beta currencies. Negative betas might be thought of as safe haven currencies. When global uncertainty is high, their returns are low because everyone rushes into those assets, driving their price up and their yields down. When global uncertainty is low, agents do not want to hold them and therefore, their yields are high. Who are they and what are their betas?

Table 10: Low and High Beta Countries, 1978Q1-2014Q2

| | | First Tertile | | | Third Tertile |
|---|---|---|---|---|---|
| Country | Beta | Excess Return | Country | Beta | Excess Return |
| Greece | -27.6 | 1.298 | Hungary | 9.5 | 5.327 |
| Portugal | -24.2 | 0.957 | Germany | 10.1 | 2.336 |
| France | -11.1 | 4.968 | Chile | 10.5 | 3.414 |
| Italy | -8.0 | 0.954 | Spain | 10.9 | 3.462 |
| Belgium | -4.0 | 6.216 | Denmark | 11.9 | 5.459 |
| Ireland | -2.8 | -0.218 | Romania | 12.1 | 10.941 |
| Philippines | -2.4 | 3.010 | Euro | 14.5 | 2.798 |
| United Kingdom | -1.3 | 4.987 | Indonesia | 15.0 | 4.818 |
| Finland | -1.2 | 3.686 | Austria | 17.0 | 5.988 |
| Israel | -0.9 | 1.580 | Mexico | 18.3 | 3.509 |
| Canada | -0.2 | 1.728 | Colombia | 26.5 | 18.066 |
| Taiwan | 0.3 | -0.236 | Turkey | 30.5 | 17.598 |
| Japan | 1.5 | 2.178 | Brazil | 36.5 | 11.837 |

Table 10 shows the individual country beta and excess return associated with the low and high tertile beta countries. Obviously, Greece, Portugal, and Italy are not thought of as safe haven currency countries now. But keep in mind that the betas are computed over different time periods. In order to gain entry to the common currency, those countries had to stabilize inflation and fiscal deficits. The identification, while not exact, shows a clear tendency for excess returns to be correlated with beta. Figure 5 shows the scatter plot for all of the currency excess returns against their betas.

Figure 5: All Mean Excess Returns and Betas

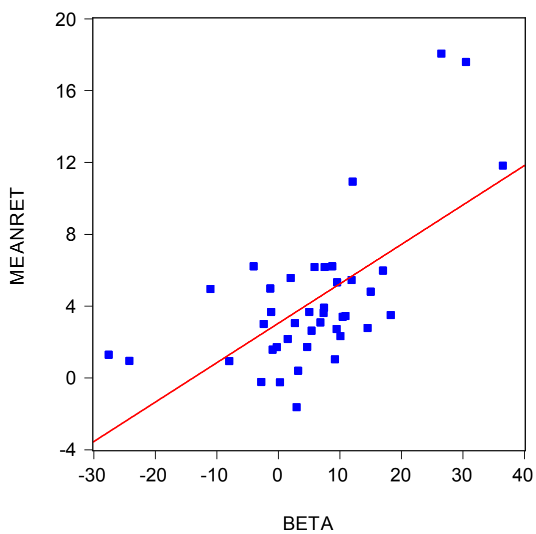
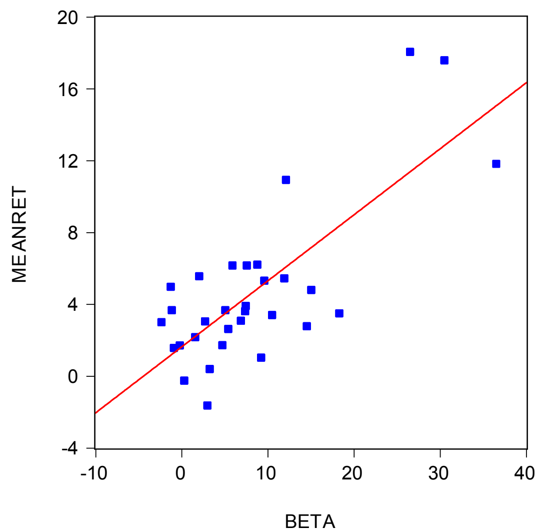



Table 11: Low and High Beta Countries (Non-Euro), 1978Q1-2014Q2

| | | First Tertile | | | Third Tertile |
|---|---|---|---|---|---|
| Country | Beta | Excess Return | Country | Beta | Excess Return |
| Philippines | -2.384 | 3.010 | Rep. South Africa | 9.201 | 1.047 |
| United Kingdom | -1.312 | 4.987 | Hungary | 9.548 | 5.327 |
| Finland | -1.188 | 3.686 | Chile | 10.461 | 3.414 |
| Israel | -0.941 | 1.580 | Denmark | 11.887 | 5.459 |
| Canada | -0.245 | 1.728 | Romania | 12.069 | 10.941 |
| Taiwan | 0.267 | -0.236 | Euro | 14.490 | 2.798 |
| Japan | 1.530 | 2.178 | Indonesia | 15.001 | 4.818 |
| New Zealand | 2.010 | 5.581 | Mexico | 18.261 | 3.509 |
| Korea | 2.681 | 3.059 | Colombia | 26.480 | 18.066 |
| Malaysia | 2.962 | -1.621 | Turkey | 30.480 | 17.598 |
| Singapore | 3.215 | 0.412 | Brazil | 36.490 | 11.837 |

In Table 11, we eliminate European countries that adopted the Euro. The identification makes a certain amount of sense. Low beta countries like Canada, Japan, and Korea were relatively safe during the global financial crisis. High beta 'countries' such as the euro zone definitely were not. Figure 6 shows, for these countries, the scatter plot of mean currency excess returns against their betas.

Figure 6: Non-Euro Mean Excess Returns and Betas




Our results share similarities with Lustig et al. (2011). In both papers the global risk factor connects with the concept of global macroeconomic uncertainty. Their relative asset pricing work identifies the HML excess currency return between $P_6$ and $P_1$ portfolios as the global risk factor, which they argued was associated with changes in global equity market volatility.

# 4 The HML $sk_t\left(UE^{gap}\right)$ Factor

The previous section showed the HML skewness of the unemployment gap to be a robust risk factor priced into carry-generated currency excess returns. We view the risk factor as a measure of global macroeconomic uncertainty, which stands in contrast to more conventional uses of volatility measures to characterize uncertainty. What does the factor look like? Which countries go into its construction? How is it related to other macro fundamentals? In this section, we address these questions.

A visual of the factor is presented in Figure 7, which plots the high, low, and high-minus low average values of skewness of the unemployment gap. Low skewness is typically negative. In these countries, there is a high probability that unemployment falls unusually fast. An increase in the HML skewness factor signifies an increase in the divergence between countries with rapidly growing unemployment and those with falling unemployment and are times of growing short-run divergence or growing inequality across countries. The figure also shows European and U.S. business cycle dating. The correspondence between the factor and U.S./European business cycles is positive only about half of the time. Since the factor samples economies beyond the U.S. and Europe, the imperfect correspondence might be expected.

Figure 7: High, Low, High-Minus-Low Unemployment Gap Skewness, U.S. and European Recessions

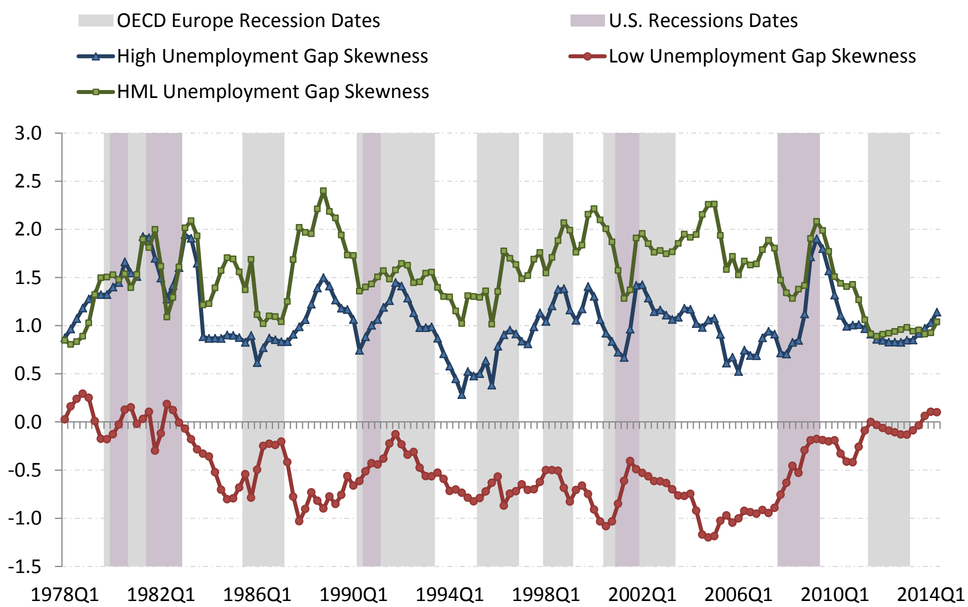



Table 12: Top Ten Countries that Appear Most Frequently in the High and Low Unemployment Gap Skewness Categories

| Country | Proportion of Times in High Group | Country | Proportion of Times in Low Group |
|---|---|---|---|
| Australia | 0.473 | Norway | 0.390 |
| Canada | 0.404 | United States | 0.295 |
| Taiwan | 0.253 | Denmark | 0.281 |
| Switzerland | 0.247 | Philippines | 0.281 |
| Singapore | 0.240 | Japan | 0.247 |
| United States | 0.212 | New Zealand | 0.240 |
| Sweden | 0.192 | Mexico | 0.205 |
| United Kingdom | 0.185 | Brazil | 0.199 |
| Mexico | 0.185 | Hungary | 0.192 |
| Poland | 0.185 | Canada | 0.185 |

What are the key countries that construct the factor? Table 12 lists the top ten countries that appear most frequently in construction of the HML unemployment gap skewness factor. They are roughly a mix of developed and emerging economies.

Table 13: Regressions of Alternative Uncertainty Measures on HML Unemployment Gap Skewness

| Dependent Variable | Coeff. | t-ratio | $R^2$ | Sample Begins |
|---|---|---|---|---|
| Log U.S. Uncertainty | -0.239 | **-3.412** | 0.091 | 1985Q1 |
| Log European Uncertainty | -0.818 | **-7.997** | 0.503 | 1997Q1 |
| Log U.K. Uncertainty | -1.132 | **-7.401** | 0.538 | 1997Q1 |
| Log VIX | 0.075 | 1.296 | 0.032 | 1990Q1 |

Notes: Bold indicates significance at 5% level.

Table 13 looks at the relation between the factor and the VIX, which is often used as a measure of uncertainty. We also look at the news-based measure of economic uncertainty constructed by Baker et al. (2015).[8] The uncertainty indices are largely based on the volume of news articles discussing economic policy uncertainty. We regress economic policy uncertainty indices for the U.S., Europe, the U.K., and the log VIX on the HML unemployment gap skewness factor. The factor is negatively (and significantly) related to the policy uncertainty indices. Evidently, policy makers are in agreement about what to do during periods of global distress. The factor is (roughly) orthogonal to the VIX.

Table 14: Correlation between HML $sk_t\,(UE^{gap})$ and Cross-Sectional Averages

| | $UE^{gap}$ | $\Delta UE$ | $y^{gap}$ | $\Delta y$ | $q^{gap}$ | $\Delta q$ | $\Delta c$ | $\pi$ |
|---|---|---|---|---|---|---|---|---|
| $sk_t\,(UE^{gap})$ | 0.214 | 0.074 | -0.122 | -0.005 | -0.053 | 0.008 | 0.119 | -0.001 |

Lastly, we show the correlation between the HML $sk_t\,(UE^{gap})$ factor and the cross-sectional average of the macro variables (Table 14). The cross-sectional average of, say GDP growth, is approximately the first principal component of the panel of GDP growth data, and corresponds to what one might be a natural measure of the global business cycle. As can be seen, there is a modest correlation with the average unemployment gap but very little correlation with the average of the other macro variables. The HML $sk_t\,(UE^{gap})$ variable evidently, does not replicate information contained in more conventional measures of the global state.

# 5 Interpretation

To provide an interpretative framework for our results, we draw on a no-arbitrage model for interest rates and exchange rates. The model is closely related to Backus et al. (2001), Brennan and Xia (2006),

[8]The data is available at their website www.policyuncertainty.com.

and Lustig et al. (2011), who extend the Cox et al. (1985) affine-yield models of the term structure to pricing currency excess returns.

The empirical work above does not say that countries with high (low) unemployment gap skewness have high (low) interest rates and pay out high (low) currency excess returns. It says investors pay attention to the HML $sk_t(UE^{gap})$ factor, which is the global risk factor. To ease notation, we will call the global risk factor $z_{g,t}$ = HML $sk_t(UE^{gap})$. We model the way investors pay attention to this global risk factor by letting the global factor ($z_{g,t}$) and a country-specific risk factor ($z_{i,t}$) load on a country's log nominal SDF ($m_{i,t+1}$) according to

$$m_{i,t+1} = -\theta_i \left(z_{i,t} + z_{g,t}\right) - u_{i,t+1}\sqrt{\omega_i z_{i,t}} - u_{gt+1}\sqrt{\kappa_i z_{i,t} + \delta_i z_{g,t}} \tag{7}$$

where

$$\begin{aligned} z_{g,t} &= \left(1-\phi_g\right)\chi_g + \phi_g z_{g,t} + u_{g,t+1}\sqrt{z_{g,t}} && (8) \\ z_{i,t} &= \left(1-\phi_i\right)\chi_i + \phi_i z_{i,t} + u_{i,t+1}\sqrt{z_{i,t}} && (9) \\ u_{g,t} &= \sigma_g v_{g,t} && (10) \\ u_{i,t} &= \sigma_i\left(\rho_i v_{g,t} + v_{i,t}\sqrt{(1-\rho_i^2)}\right) && (11) \end{aligned}$$

and $v_{g,t}$ and $v_{i,t}$ are independent standard normal variates. Since the global factor must be built from an aggregation of country factors, we allow the country-specific innovation to be correlated with the global innovation $E\left(u_{i,t}u_{g,t}\right) = \rho_i$.

The conditional mean ($\mu_{i,t}$) and conditional variance ($V_{i,t}$) of the log SDF are

$$\begin{aligned} &\mu_{i,t} = -\theta_i\left(z_{i,t} + z_{g,t}\right) \\ &V_{i,t} = \sigma_g^2\delta_i z_{g,t} + \left(\sigma_g^2\kappa_i + \sigma_i^2\omega_i\right) z_{i,t} + 2\sigma_g\sigma_i\rho_i\sqrt{\omega_i z_{i,t}}\sqrt{\kappa_i z_{i,t} + \delta_i z_{g,t}}. \end{aligned}$$

From investor Euler equations, we obtain the pricing relationships

$$\begin{aligned} r_{i,t} &= \mu_{i,t} + 0.5V_{i,t} \\ \Delta s_{i,t} &= m_{i,t} - m_{0,t} \\ R^e_{i,t+1} &= 0.5\left(V_{0,t} - V_{i,t}\right) + \epsilon_{i,t+1} \end{aligned}$$

where $R^e_{i,t+1} = \Delta s_{i,t+1} + r_{i,t} - r_{0,t}$ is the excess dollar return. The last equation comes from $E_t\left(R^e_{i,t+1}\right) = 0.5\left(V_{0,t} - V_{i,t}\right)$ and $\epsilon_{i,t+1}$ is the expectational error.

Countries with high $\mu_{i,t}$ and $V_{i,t}$ will have high interest rates. But for country $i$ to also pay the carry-trade excess return, it must have low $V_{i,t}$ relative to $V_{0,t}$. This suggests a pattern of high $\mu_{i,t}$ and low $V_{i,t}$ to explain the data. The usual story is one of the precautionary saving motive. If $V_{i,t}$ is low relative to $V_{0,t}$, there is little need for precautionary saving. Bond prices in $i$ will therefore be low and yields high. We note that heterogeneity in the risk-factor loadings on the log SDFs is not necessary to generate differences in conditional variances. Differences in the realizations of country-specific risk $z_{i,t}$ will do that. What is key, however, is that the log SDFs load on the global factor $z_{gt}$. If they do not, excess currency returns may be non zero, but they will not be priced by the global risk factor.

We estimate the model by simulated method of moments. We begin by estimating the process for the global risk factor (the HML skewness of the unemployment gap) $z_{g,t}$ separately. Parameters in equation (8) are estimated by simulated method of moments and are shown in Table 15.

Table 15: SMM Estimates of the Global Risk Factor Process

| | $\chi_g$ | $\phi_g$ | $\sigma_g$ |
|---|---|---|---|
| Estimate | 1.527 | 0.871 | 0.394 |
| t-ratio | 21.651 | 12.916 | 10.595 |

Notes: The moments used in estimation include $E\left(z_{g,t}\right)$, $E\left(z_{g,t}^2\right)$, $E\left(z_{g,t}z_{g,t-1}\right)$, $E\left(z_{g,t}z_{g,t-2}\right)$, $E\left(z_{g,t}^2 z_{g,t-1}^2\right)$, and $E\left(z_{g,t}z_{g,t-2}^2\right)$.

Recall that we do not have a balanced panel. The time-span coverage varies by availability. Our data consists of 41 countries that can be bilaterally paired with the U.S. (country '0'). Of these 41 countries, we have data on 38 with sufficiently long time-series to estimate. Estimation is done bilaterally. The 14 moments we use in estimation are $E\left(h_{i,t}\right)$ where

$$h_{i,t}' = \left(\Delta s_{i,t}, \Delta s_{i,t}^2, \Delta s_{i,t}\Delta s_{i,t-1}, \Delta s_{i,t}\Delta s_{i,t-4}, R_{i,t}^e, \left(R_{i,t}^e\right)^2, R_{i,t}^e R_{i,t-1}^e, R_{i,t}^e R_{i,t-4}^e, r_{i,t}, r_{i,t}^2, r_{i,t}r_{i,t-1}, r_{0,t}, r_{0,t}^2, r_{0,t}r_{0,t-1}\right).$$

Table 16 shows the cross-sectional average of the parameter estimates. Note that there is substantial heterogeneity across individual estimates. The innovation to the U.S. specific risk factor is more highly correlated with the innovation to the global factor than the innovations (on average) to the other countries. The U.S. log SDF loads more heavily on the global risk factor $\delta$ than other countries, while other countries load more heavily on their country-specific risk factors $\kappa$.

Table 16: SMM Parameter Estimates

| Parameter | Average Foreign Country | United States |
|---|---|---|
| $\chi$ | 1.120 | 0.502 |
| $\phi$ | 0.817 | 0.709 |
| $\sigma$ | 0.198 | 0.605 |
| $\theta$ | -0.612 | -0.286 |
| $\omega$ | 0.070 | 0.211 |
| $\kappa$ | 2.442 | 1.015 |
| $\delta$ | 1.427 | 2.832 |
| $\rho$ | 0.113 | 0.347 |

Next, we simulate the estimated model. In each of the 2,000 simulations, we generate 87 observations on exchange rate returns and interest rates across the 38 countries and the United States. In the data, we had, on average, 87 time-series observations. For each replication, we sort currencies into six interest rate ranked portfolios, compute their mean excess (over the U.S.) returns and Sharpe ratios, and estimate the single-factor beta-risk model. Table 17 reports the median values over the 2,000 simulations.

Table 17: Excess Returns and Two-Pass Estimation of the Single-Factor Beta-Risk Model on Simulated Carry Excess Returns

| Panel A: Test Excess Return Summary Statistics. | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ | |
| Mean Excess | -3.042 | 0.661 | 2.355 | 5.384 | 10.185 | 19.706 | |
| Sharpe Ratio | -1.648 | 0.456 | 1.251 | 1.873 | 2.623 | 2.844 | |
| **Panel B: Single-Factor Model.** | | | | | | | |
| | $\lambda$ | t-ratio | $\gamma$ | t-ratio | $R^2$ | Test-stat | p-val. |
| SDF | 2.946 | **11.179** | 1.082 | 1.589 | 0.982 | 11.950 | 0.035 |

The model is actually too successful in generating currency excess returns. The mean excess returns increase monotonically across the six portfolios. The mean excess returns on the simulated $P_5$ is about the same as the sixth quantile of returns in the data. The model does not generate enough volatility in returns as the Sharpe ratios are too high. The model-generated estimates for the beta-risk model qualitatively conforms to the data. The price of risk $\lambda$ is positive and significant, the constant is insignificant, and the $R^2$ is similar to what we estimated in the data.

# 6 Conclusion

It has long been understood that systematic currency excess returns (deviations from uncovered interest parity) are available to investors. Less well understood is what are the risks being compensated for by the excess returns.

In a financially integrated world, excess returns should be driven by common factors. We find that a global risk factor, constructed as the high-minus-low conditional skewness of the unemployment gap, is priced into carry-trade generated excess returns. Carry trade generated currency excess returns compensate for global macroeconomic risks.

There are three notable features of this risk factor. First, it is a macroeconomic fundamental variable. As Lustig and Verdelhan (2011) point out, the statistical link between asset returns and macroeconomic factors is always weaker than the link between asset returns and return based factors, so the high explanatory power provided by this factor and its significance is notable. Second, the factor is global in nature. It is constructed from averages of countries in the top and bottom quartiles of unemployment gap skewness. Since the portfolios of carry generated excess returns are available to global investors, only global risk factors should be priced. Third, the factor measures something different from standard measures of global uncertainty. Unlike the standard measures of uncertainty, the HML global macro risk factor can capture asymmetries in the distribution of the global state which reflects the divergence, disparity, and inequality of fortunes across countries.

# References


[1] Ang, Andrew and Joseph S. Chen. 2010. "Yield Curve Predictors of Foreign Exchange Returns," mimeo, Columbia University.

[2] Backus, David K., Silverio Foresi, and Chris I. Telmer. 2002. "Affine Term Structure Models and the Forward Premium Anomaly." *Journal of Finance*, 56, 279-304.

[3] Baker, Scott R., Nicholas Bloom, and Steven J. Davis. 2015. "Measuring Economic Policy Uncertainty," www.policyuncertainty.com.

[4] Bansal, Ravi and Ivan Shaliastovich. 2012. "A Long-Run Risks Explanation of Predictability Puzzles in Bond and Currency Markets." *Review of Financial Studies,* 26, pp. 1-33.

[5] Bilson, John F.O. 1981. "The 'Speculative Efficiency' Hypothesis." *Journal of Business*, 54, pp. 435-51.

[6] Brennan M.J., and Y. Xia, 2006. "International Capital Markets and Foreign Exchange Risk," *Review of Financial Studies*, 19, 753–95.

[7] Brunnermeier, Markus K., Stefan Nagel, and Lasse Pedersen. 2009. "Carry Trades and Currency Crashes." *NBER Macroeconomics Annual*, 2008, 313-347.

[8] Burnside, C. 2011a. "The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk: Comment," *American Economic Review,* 101, 3456–3476.

[9] Burnside, C. 2011b. "The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk: Appendix," Online Appendix,
https://www.aeaweb.org/articles.php?doi=10.1257/aer.101.7.3456.

[10] Burnside, Craig, Martin Eichenbaum, Isaac Kleshchelski, and Sergio Rebelo. 2011. "Do Peso Problems Explain the Returns to the Carry Trade?" *Review of Financial Studies*, 24, 853-891.

[11] Chinn, Menzie and Guy Merideth, 2004."Monetary Policy and Long Horizon Uncovered Interest Parity,"*IMF Staff Papers*, 51, 409-430.

[12] Christiansen, Charlott, Angelo Ranaldo and Paul Söderlind, 2011. "The Time-Varying Systematic Risk of Carry Trade Strategies," *Journal of Financial and Quantitative Analysis*, 46, 1107–25.

[13] Clarida, Richard, Josh Davis, and Niels Pederson. 2009. "Currency Carry Trade Regimes: Beyond the Fama Regression," *Journal of International Money and Finance,* 28, pp. 1365-1389.

[14] Cochrane, John H. 2005. *Asset Pricing*. Princeton and Oxford: Princeton University Press.

[15] Colacito, Riccardo and Marian M. Croce. 2011. "Risks for the Long Run and the Real Exchange Rate." *Journal of Political Economy*, 119, 153-182.

[16] Cox, J. C., J. E. Ingersoll, and S. A. Ross, 1985.“A Theory of the Term Structure of Interest Rates,” *Econometrica*, 53:385408.

[17] Cumby, Robert E. 1988. “Is it Risk? Explaining Deviations from Uncovered Interest Parity,” *Journal of Monetary Economics*, 22, 279-99.

[18] Daniel, Kent, Robert J. Hodrick, and Zhongjin Lu, 2014. “The Carry Trade: Risks and Drawdonwns,” NBER Working Paper 20433.

[19] Engel, Charles. 1996. “The Forward Discount Anomaly and the Risk Premium: A Survey of Recent Evidence.” *Journal of Empirical Finance*, 3, 123-192.

[20] Epstein Lawrence and Stanley Zin. 1989. “Substitution, Risk Aversion and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework,” *Econometrica*, 57, 937-969.

[21] Fama, Eugene F. 1984. “Forward and Spot Exchange Rates.” *Journal of Monetary Economics*, 14, 319-338.

[22] Frankel, Jeffrey A. and Charles Engel. 1984. “Do Asset-Demand Functions Optimize over the Mean and Variance of Real Returns? A Six-Currency Test,” *Journal of International Economics*, 17, 309-323.

[23] Hansen, Lars P. and Robert J. Hodrick. 1980. “Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis,” *Journal of Political Economy*, 88(5), 829–853.

[24] Hassan, Tarek A, 2013. “Country Size, Currency Unions, and International Asset Returns,” *Journal of Finance*, 68, 2269–2308.

[25] Hassan, Tarek A. and Rui C. Mano. 2014. “Forward and Spot Exchange Rates in a Multi-currency World,” NBER Working paper w20294.

[26] Hodrick, Robert J. 1987. *The Empirical Evidence on the Efficiency of Forward and Futures Foreign Exchange Markets,* Chur: Harwood.

[27] Hodrick, Robert J. and Edward C. Prescott. 1997. “Postwar U.S. Business Cycles: An Empirical Investigation,” *Journal of Money, Credit and Banking*, 29, 1-16.

[28] Jordà, Òscar and Alan M. Taylor. 2012. “The Carry Trade and Fundamentals: Nothing to Fear but FEER itself.” *Journal of International Economics*, 88, pp. 74-90.

[29] Lee, Bong-Soo and Beth Fisher Ingram, 1991. “Simulation Estimation of Time-Series Models,” *Journal of Econometrics* 47, 197-205.

[30] Lewis, Karen K. 1995. ”Puzzles in International Financial Markets,” in G. Grossman and K. Rogoff, eds. *Handbook of International Economics* (North Holland: Amsterdam).

[31] Lustig, Hanno and Adrien Verdelhan. 2007. "The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk." *American Economic Review*, 97, 89-117.

[32] Lustig, Hanno and Adrien Verdelhan. 2012. "Exchange Rates in a Stochastic Discount Factor Framework", with Hanno Lustig, in *Handbook of Exchange Rates*, Jessica James, Ian W. Marsh, and Lucio Sarno, eds., Wiley.

[33] Lustig, Hanno, Nikolai Roussanov, and Adrien Verdelhan. 2011. "Common Risk Factors in Currency Markets." *Review of Financial Studies*, 24, 3731-3777.

[34] Mark, Nelson C. 1985. "On Time Varying Risk Premia in the Foreign Exchange Market: An Econometric Analysis," *Journal of Monetary Economics*, 16, 3-18.

[35] Mark, Nelson C. 1988. "Time-Varying Betas and Risk Premia in th Pricing of Forward Foreign Exchange Contracts," *Journal of Financial Economics*, 22, 335-54.

[36] Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf. 2012. "Carry Trades and Global Foreign Exchange Volatility." *Journal of Finance*, 67, 681-718.

[37] Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf. 2013. "Currency Risk Premia and Macro Fundamentals," *mimeo,* Cass Business School, City University London.

[38] Newey, Whithey K. and Kenneth D. West. 1987. "A Simple, Positive Semidefinite, Heteroskedasticity adn Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703-708.

[39] Ready, Robert, Nikolai Roussanov, and Colin Ward, 2015. "After the Tide: Commodity Currencies and Global Trade," *mimeo*, University of Pennsylvania.

[40] Verdelhan, Adrien. 2010. "A Habit-Based Explanation of the Exchange Rate Risk Premium." *The Journal of Finance*, 65, 123-146.

[41] Weil, Philippe. 1989. "The Equity Premium Puzzle and the Risk-Free Rate Puzzle," *Journal of Monetary Economics*, 24, 401-421.

# Appendix

## Additional notes on the data

All interest rates are for 3-months maturity.

Australia: 73.1-86.1, 3 month T-bill rate. 86.2-14.2, 3 month interbank rate.

Austria: 91.2-98.4, EIBOR (Emirates Interbank Offer Rate, *Datastream*).

Belgium: 73.1-89.4, 3 month eurocurrency (Harris). 90.1-98.4, EIBOR.

Brazil: 04.1-14.2, Imputed from spot and forward rates (*Datastream*).

Canada: 73.1-96.1, 3 month eurocurrency. 96.2-14.2, 3-month T-bill rate.

Chile: 04.1-13.2, Imputed from spot and forward rates.

Colombia: 04.1-13.2, Imputed from spot and forward rates.

Czech Republic: 92.2-14.2, Interbank rate.

Denmark: 84.4-88.1, imputed from spot and forward rates. 88.2-14.2, Interbank rate.

Spain: 88.3-98.4, Interbank.

Euro zone: 99.1-14.2, Interbank rate, Germany.

Finland: 87.1-98.4, EIBOR.

France: 73.1-96.1, 3-month eurocurrency. 96.2-98.4, EIBOR.

Great Britain: 73.1-96.1, 3-month eurocurrency. 96.2-98.4, UK Interbank.

Greece: 94.2-98.4. Interbank.

Germany: 73.1-96.1, 3-month eurocurrency. 96.2-98.4, EIBOR.

Hungary: 95.3-14.2: Interbank.

Iceland: 95.3-00.1, Interbank mid-rate. 00.2-14.2, Reykjavik interbank offer rate.

Indonesia: 96.1-14.2, Interbank rate.

India: 97.4-98.3, Imputed from spot and forward rates. 98.4-14.2 Interbank.

Ireland: 84.1-98.4. Interbank.

Israel: 94.4-99.3, T-bill. 99.4-14.2, Interbank.

Italy: 73.1-96.1, 3-month eurocurrency. 96.2-98.4, EIBOR.

Japan: 73.1-96.1, 3-month eurocurrency. 96.2-14.2, Interbank.

Korea: 92.1-14.2. Interbank.

Malaysia: 93.3-14.2, Interbank.

Mexico: 78.1-14.2, T-bill (FRED).

Netherlands: 73.1-96.1, 3-month eurocurrency. 96.2-98.4, EIBOR.

Norway: 86.1-14.2. Interbank.

New Zealand: 74.1-13.4, Interbank (FRED).

Philippines: 87.1-14.2 T-bill.

Poland: 94.4-14.2 Interbank.

Portugal: 96.4-98.4, Imputed from spot and forward.

Romania: 95.3-14.2. Interbank.

Republic of South Africa: 73.1-14.3. T-bill.

Singapore: 84.4-87.2: Imputed from spot and forward rates. 87.3-13.4, Interbank.

Switzerland: 73.1-96.1, 3-month eurocurrency. 96.2-14.2, Interbank.

Sweden: 84.4-86.4, Imputed from spot and forward rates. 87.1-14.3, Interbank.

Thailand: 95.1-96.3, imputed from spot and forward rates. 96.5-14.2, Interbank.

Turkey: 96.4-06.4, imputed from spot and forward rates. 07.1-14.2, Interbank.

Taiwan: 82.2-14.2, Money market rates.

### Two-pass regression procedure and GMM standard errors

We have $k$ factors, $T$ time-series observations and $n$ excess returns (assets). Vectors are underlined. Matrices are bolded. Scalars have no special designation. The objective is to estimate the $k-$factor 'beta-risk' model

$$E\left(r_{i,t}^{e}\right) = \underline{\beta}_i'\underline{\lambda} + \alpha_i \tag{12}$$

where $\underline{\beta}_i$ is a $k-$dimensional vector of the factor betas for excess return $i$ and $\underline{\lambda}$ is the $k-$dimensional vector of factor risk premia. The expectation is taken over $t$. The beta-risk model's answer to the question as to why average returns vary across assets is that returns with high betas (covariance with a factor) pay a high risk premiums ($\underline{\lambda}$). The cross-sectional test can be implemented with a two-pass procedure. Let $\underline{f}_t$ be the $k-$dimensional vector of the macro factors. In the first pass for each excess return $i = 1, ..., n$, estimate the factor betas in the time-series regression,

$$r_{i,t}^{e} = a_i + \underbrace{(\beta_{1,i}, ..., \beta_{k,i})}_{\underline{\beta}_i'} \begin{pmatrix} f_{1,t} \\ \vdots \\ f_{k,t} \end{pmatrix} + \epsilon_{i,t} = \underline{\tilde{\beta}}_i'\underline{F}_t + \epsilon_{i,t}$$

where

$$\underline{F}_t = \begin{pmatrix} 1 \\ \underline{f}_t \end{pmatrix}, \ \underline{f}_t = \begin{pmatrix} f_{1,t} \\ \vdots \\ f_{k,t} \end{pmatrix}, \ \underset{(k+1)\times 1}{\underline{\tilde{\beta}}_i} = \begin{pmatrix} a_i \\ \underline{\beta}_i \end{pmatrix}, \ \underset{(k\times 1)}{\underline{\beta}_i} = \begin{pmatrix} \beta_{1,i} \\ \vdots \\ \beta_{k,i} \end{pmatrix}.$$

In the second pass, we can run the cross-sectional regression of average returns $\bar{r}_i^e = (1/T)\sum_{t=1}^{T} r_{i,t}^e$, using the betas as data, to estimate the factor risk premia, $\underline{\lambda}$. If the excess return's covariance with the factor is systematic and undiversifiable, that covariance risk should be 'priced' into the return. The factor risk premium should not be zero. The second-pass regression run with a constant is,

$$\bar{r}_i^e = \gamma + \underbrace{(\lambda_1, ..., \lambda_k)}_{\underline{\lambda}} \begin{pmatrix} \beta_{1,i} \\ \vdots \\ \beta_{k,i} \end{pmatrix} + \alpha_i = \gamma + \underline{\lambda}'\underline{\beta}_i + \alpha_i$$

The $\alpha_i$ are the pricing errors. When the cross-sectional regression is run without a constant, set $\gamma = 0$.

$$\underline{\bar{r}}_i^e = \gamma + \underline{\beta}_i'\underline{\lambda} + \alpha_i.$$

OLS standard errors give asymptotically incorrect inference because the $\beta s$ are not data but are generated regressors. Cochrane (2001) describes a procedure to obtain GMM standard errors that delivers asymptotically valid inference that is robust to the generated regressors problem and robust to heteroskedasticity and autocorrelation in the errors. Cochrane's strategy is to use the standard errors from a GMM estimation problem that exactly reproduces the two-stage regression point estimates. We will need the following notation

$$
\begin{aligned}
\underset{(k\times k)}{\mathbf{\Sigma}_f} &= E\left(\underline{f}_t - \underline{\mu}_f\right)\left(\underline{f}_t - \underline{\mu}_f\right)', \\
\underline{\epsilon}_t &= (\epsilon_{1,t}, \epsilon_{2,t}, ..., \epsilon_{n,t})' \\
\underset{n\times n}{\mathbf{\Sigma}} &= E\left(\underline{\epsilon}_t \underline{\epsilon}_t'\right) \\
\underset{n\times k}{\mathbf{B}} &= \begin{pmatrix} \underline{\beta}_1' \\ \vdots \\ \underline{\beta}_n' \end{pmatrix} = \begin{pmatrix} \beta_{1,1} & \cdots & \beta_{k,1} \\ \vdots & & \vdots \\ \beta_{1,n} & \cdots & \beta_{k,n} \end{pmatrix} \\
\underset{k\times n}{\mathbf{A}} &= \underset{k\times k}{(\mathbf{B}'\mathbf{B})}^{-1} \underset{k\times n}{\mathbf{B}'} \\
\underset{n\times n}{\mathbf{M}_\beta} &= \mathbf{I}_n - \underset{n\times k}{\mathbf{B}} \underset{k\times k}{(\mathbf{B}'\mathbf{B})}^{-1} \underset{k\times n}{\mathbf{B}}{}' \\
\underset{n\times(k+1)}{\mathbf{X}} &= (\underline{\iota}_n \ \mathbf{B}'), \text{ where } \underline{\iota}_n = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \leftarrow n'\text{th row} \\
\underset{(k+1)\times n}{\mathbf{C}} &= \underset{(k+1)\times(k+1)}{(\mathbf{X}'\mathbf{X})}^{-1} \underset{(k+1)\times n}{\mathbf{X}'} \\
\underset{n\times n}{\mathbf{M}_X} &= \mathbf{I}_n - \underset{n\times(k+1)}{\mathbf{X}} \underset{(k+1)\times(k+1)}{(\mathbf{X}'\mathbf{X})^{-1}} \underset{(k+1)\times n}{\mathbf{X}'} \\
\underset{(k+1)\times(k+1)}{\tilde{\mathbf{\Sigma}}_f} &= \begin{pmatrix} \underset{\text{scalar}}{0} & \underset{1\times k}{\underline{0}} \\ \underset{k\times 1}{\underline{0}} & \underset{k\times k}{\mathbf{\Sigma}_f} \end{pmatrix}
\end{aligned}
$$

*Estimation without the constant.* When estimating without the constant in the second-pass regression, the parameter vector is

$$
\underset{[k(n+1)+k]\times 1}{\underline{\theta}} = \begin{pmatrix} \tilde{\underline{\beta}}_1 \\ \vdots \\ \tilde{\underline{\beta}}_n \\ \underline{\lambda} \end{pmatrix} = \begin{pmatrix} a_1 \\ \underline{\beta}_1 \\ \vdots \\ a_n \\ \underline{\beta}_n \\ \underline{\lambda} \end{pmatrix}
$$

Let the second moment matrix of the factors be

$$
\underset{(k+1)\times(k+1)}{\mathbf{M}_F} = \frac{1}{T}\sum_{t=1}^{T} \underline{F}_t \underline{F}_t'
$$

The moment conditions are built off of the error vector,

$$\underset{n(k+2)\times 1}{\underline{u}_t(\theta)} = \begin{pmatrix} \underline{F}_t\left(r^e_{1,t}-\underline{F}'_t\underline{\tilde{\beta}}_1\right) \\ \vdots \\ \underline{F}_t\left(r^e_{n,t}-\underline{F}'_t\underline{\tilde{\beta}}_n\right) \\ r^e_{1,t}-\underline{\beta}'_1\underline{\lambda} \\ \vdots \\ r^e_{n,t}-\underline{\beta}'_n\underline{\lambda} \end{pmatrix} = \begin{pmatrix} \underline{F}_t\left(r^e_{1,t}-\underline{F}'_t\underline{\tilde{\beta}}_1\right) \\ \vdots \\ \underline{F}_t\left(r^e_{n,t}-\underline{F}'_t\underline{\tilde{\beta}}_n\right) \\ \underline{R}^e_t-\mathbf{B}\underline{\lambda} \end{pmatrix} \begin{matrix} \\ \\ \leftarrow \text{row } n(k+1) \\ \leftarrow (n\times 1) \end{matrix}$$

where

$$\underline{r}^e_t = \begin{pmatrix} r^e_{1,t} \\ \vdots \\ r^e_{n,t} \end{pmatrix}$$

Let

$$\underline{g}_T(\underline{\theta}) = \frac{1}{T}\sum_{t=1}^{T}\underline{u}_t(\theta)$$

$$\underset{[n(k+1)]\times[n(k+1)+k]}{\mathbf{d}_T} = \frac{\partial \mathbf{g}_T(\underline{\theta})}{\partial \underline{\theta}'} = \begin{pmatrix} \underset{[n(k+1)]\times[n(k+1)]}{-\mathbf{I}_n\otimes\mathbf{M}_F} & \underset{[n(k+1)]\times k}{\mathbf{0}} \\ \underset{n\times[n(k+1)]}{-\mathbf{I}_n\otimes\begin{pmatrix}\underset{\text{scalar}}{0} & \underline{\lambda}'\end{pmatrix}} & \underset{n\times k}{-\mathbf{B}} \end{pmatrix}$$

To replicate the estimates in the two-pass procedure, we need[9]

$$\underset{[n(k+1)+k]\times[n(k+2)]}{\mathbf{a}_T} = \begin{pmatrix} \mathbf{I}_{n(k+1)} & \underset{n(k+1)\times n}{\mathbf{0}} \\ \underset{k\times n(k+1)}{\mathbf{0}} & \underset{k\times n}{\mathbf{B}'} \end{pmatrix}, \tag{13}$$

[9] In the usual GMM problem, we minimize

$$\underline{g}_T(\underline{\theta})'\,\mathbf{S}_T^{-1}\underline{g}_T(\underline{\theta})$$

where

$$\mathbf{S}_T \overset{a.s.}{\to} \mathbf{S} = \mathbf{E}\left(\sum_{j=-\infty}^{\infty}\underline{u}_t(\underline{\theta})\,\underline{u}_{t-j}(\theta)'\right)$$

We do Newey-West on $\underline{u}_t(\theta)$ to get $\mathbf{S}_T$. We will want to plug in our estimated $\lambda$ and $\beta s$ into $\mathbf{d}_T$. This problem chooses $\underline{\theta}$ to set

$$\mathbf{d}_T\mathbf{S}_T^{-1}\underline{g}_T(\underline{\theta}) = \underline{0}$$

and can be recast as having a weighting matrix on the moment conditions

$$\mathbf{a}_T\underline{g}_T(\underline{\theta}) = 0$$

where

$$\mathbf{a}_T = \mathbf{d}_T\mathbf{S}_T^{-1}$$

The covariance matrix of $\underline{\theta}$ for this problem is,

$$\mathbf{V}_\theta = \frac{1}{T}\,(\mathbf{d}_T\mathbf{S}_T\mathbf{d}_T)^{-1}$$

but this is not the covariance matrix for the two-pass estimation problem. The reason is that the last set of $n$ moment conditions in $\mathbf{g}_T(\underline{\theta})$ isn't the cross-sectional regression estimated by least squares (which is $\mathbf{B}'\left(\frac{1}{T}\sum_{t=1}^{T}\underline{R}^e_t-\mathbf{B}\underline{\lambda}\right)$).

not $\mathbf{d}_T\mathbf{S}_T^{-1}$. The coefficient covariance matrix we want is

$$\mathbf{V}_\theta = \frac{1}{T}\left(\mathbf{a}_T\mathbf{d}_T\right)^{-1}\left(\mathbf{a}_T\mathbf{S}_T\mathbf{a}_T'\right)\left[\left(\mathbf{a}_T\mathbf{d}_T\right)^{-1}\right]' \tag{14}$$

To test if the pricing errors are zero, use the covariance matrix of the moment conditions,

$$\mathbf{V}_g = \frac{1}{T}\left(\mathbf{I}_{(n(k+1))} - \mathbf{d}_T\left(\mathbf{a}_T\mathbf{d}_T\right)^{-1}\mathbf{a}_T\right)\mathbf{S}_T\left(\mathbf{I}_{(n(k+2))} - \mathbf{d}_T\left(\mathbf{a}_T\mathbf{d}_T\right)^{-1}\mathbf{a}_T\right) \tag{15}$$

We want to get $\mathbf{V}_\theta$ and $\mathbf{V}_g$ by plugging in.

**GMM standard errors when estimating with a constant.** The cross-sectional regression is now

$$\frac{1}{T}\sum_{t=1}^{T} r_{i,t}^e = \gamma + \underline{\beta}_i'\underline{\lambda} + \alpha_i$$

where $\gamma$ is the constant. We have to add $\gamma$ to the coefficient vector $\theta$. Place it according to

$$\underset{(n+1)(k+1)\times 1}{\underline{\theta}} = \begin{pmatrix} a_1 \\ \underline{\beta}_1 \\ \vdots \\ a_n \\ \underline{\beta}_n \\ \gamma \\ \underline{\lambda} \end{pmatrix} = \begin{pmatrix} \underline{\tilde{\beta}}_1 \\ \vdots \\ \underline{\tilde{\beta}}_n \\ \gamma \\ \underline{\lambda} \end{pmatrix}$$

Define

$$\mathbf{X} = \begin{pmatrix} \underset{n\times 1}{\underline{\iota}} & \underset{n\times k}{\mathbf{B}} \end{pmatrix}$$

The error vector that defines the model is

$$\underline{u}_t\left(\underline{\theta}\right) = \begin{pmatrix} \underline{F}_t\left(r_{1,t}^e - \underline{F}_t'\underline{\tilde{\beta}}_1\right) \\ \vdots \\ \underline{F}_t\left(r_{n,t}^e - \underline{F}_t'\underline{\tilde{\beta}}_n\right) \\ r_{1,t}^e - \gamma - \underline{\beta}_1'\underline{\lambda} \\ \vdots \\ r_{n,t}^e - \gamma - \underline{\beta}_n'\underline{\lambda} \end{pmatrix} = \begin{pmatrix} \underline{F}_t\left(r_{1,t}^e - \underline{F}_t'\underline{\tilde{\beta}}_1\right) \\ \vdots \\ \underline{F}_t\left(r_{n,t}^e - \underline{F}_t'\underline{\tilde{\beta}}_n\right) \\ \underline{R}_t^e - \mathbf{X}\begin{pmatrix} \gamma \\ \underline{\lambda} \end{pmatrix} \end{pmatrix}$$

Do Newey and West on $\underline{u}_t\left(\theta\right)$ to get $\mathbf{S}_T$. Use

$$\underset{[(n+1)(k+1)]\times[n(k+2)]}{\mathbf{a}_T} = \begin{pmatrix} \mathbf{I}_{n(k+1)} & \underset{[n(k+1)]\times n}{\mathbf{0}} \\ \underset{(k+1)\times[n(k+1)]}{\mathbf{0}} & \underset{(k+1)\times n}{\mathbf{X}'} \end{pmatrix}$$

$$\underset{[n(k+1)]\times[(k+1)(n+1)]}{\mathbf{d}_T} = \frac{\partial \mathbf{g}_T\left(\underline{\theta}\right)}{\partial \underline{\theta}'} = \begin{pmatrix} \underset{[n(k+1)]\times[n(k+1)]}{-\mathbf{I}_n \otimes \mathbf{M}_F} & \underset{[n(k+1)]\times(k+1)}{\mathbf{0}} \\ \underset{n\times[n(k+1)]}{-\mathbf{I}_n \otimes \begin{pmatrix} \underset{\text{scalar}}{0} & \underline{\lambda}' \end{pmatrix}} & \underset{n\times(k+1)}{-\mathbf{X}} \end{pmatrix}$$

to plug into (14) and (15).

We do not use GMM to estimate the model. We use the two-step procedure to get the point estimates for the betas and lambdas and plug those estimates into the GMM formulae to get standard errors.

# Alternative Window Sizes

This section reports estimation of the beta model when the relevant moments are computed with windows of 16 and 24 quarters.

Table 18: Two-Pass Estimation of the Single-Factor Beta-Risk Model on Carry Excess Returns, 1977Q1-2014Q2

| | | | Single-Factor Model. | | | | |
|---|---|---|---|---|---|---|---|
| HML Factor | $\lambda$ | t-ratio | $\gamma$ | t-ratio | $R^2$ | Test-stat | p-val. |
| $sk_t(UE^{gap})$ | 0.530 | **3.561** | 3.186 | 1.295 | 0.969 | 2.427 | 0.787 |
| $sk_t(\Delta UE)$ | 0.816 | **2.264** | 3.215 | 0.786 | 0.995 | 0.095 | 1.000 |
| $sk_t(\Delta y)$ | 0.427 | **2.580** | 5.480 | 1.930* | 0.677 | 5.141 | 0.399 |
| $sk_t(y^{gap})$ | 0.382 | **2.166** | 7.108 | **2.639** | 0.172 | 7.179 | 0.208 |
| $sk_t(\Delta c)$ | 0.592 | **2.317** | 7.672 | **1.990** | 0.630 | 2.513 | 0.775 |
| $sk_t(\pi)$ | -0.172 | -1.314 | 5.188 | **2.376** | 0.027 | 9.919 | 0.078 |
| $sk_t(q^{gap})$ | 0.876 | 1.797* | 6.720 | 1.679* | 0.250 | 3.823 | 0.575 |
| $sk_t(\Delta q)$ | 0.769 | **2.332** | 7.185 | **2.640** | 0.773 | 4.416 | 0.491 |
| $\sigma_t(UE^{gap})$ | 4.273 | **2.373** | 5.548 | 1.599 | 0.603 | 6.371 | 0.272 |
| $\sigma_t(\Delta UE)$ | 0.013 | 0.470 | 3.857 | **2.553** | 0.002 | 11.348 | 0.045 |
| $\sigma_t(\Delta y)$ | 2.093 | **2.737** | 1.216 | 0.341 | 0.967 | 1.117 | 0.953 |
| $\sigma_t(y^{gap})$ | 1.058 | **2.659** | 1.514 | 0.389 | 0.927 | 2.330 | 0.802 |
| $\sigma_t(\Delta c)$ | 2.079 | **2.386** | -1.326 | -0.282 | 0.890 | 1.730 | 0.885 |
| $\sigma_t(\pi)$ | 4.615 | **2.464** | 2.265 | 0.740 | 0.846 | 2.787 | 0.733 |
| $\sigma_t(q^{gap})$ | -6.824 | -1.203 | 5.959 | 1.031 | 0.320 | 1.951 | 0.856 |
| $\sigma_t(\Delta q)$ | 9.611 | **2.933** | 3.728 | 1.340 | 0.923 | 3.068 | 0.690 |
| $\mu_t(UE^{gap})$ | 4.242 | **2.718** | 4.632 | 1.065 | 0.818 | 3.330 | 0.649 |
| $\mu_t(\Delta UE)$ | 0.121 | **2.634** | 3.888 | 0.826 | 0.812 | 2.755 | 0.738 |
| $\mu_t(\Delta y)$ | -1.999 | **-2.465** | 2.496 | 0.718 | 0.970 | 0.635 | 0.986 |
| $\mu_t(y^{gap})$ | 0.981 | **2.788** | 3.840 | 1.011 | 0.796 | 3.096 | 0.685 |
| $\mu_t(\Delta c)$ | -1.453 | **-3.327** | 1.327 | 0.497 | 0.986 | 0.482 | 0.993 |
| $\mu_t(\pi)$ | 9.620 | **2.865** | 3.016 | 1.246 | 0.913 | 2.998 | 0.700 |
| $\mu_t(q^{gap})$ | 2.099 | **2.142** | 3.048 | 0.709 | 0.532 | 2.643 | 0.755 |
| $\mu_t(\Delta q)$ | 4.726 | 1.842* | -0.373 | -0.074 | 0.674 | 2.027 | 0.845 |

Notes: The raw data are quarterly (1973Q1 to 2014Q2) and when available are end-of-quarter and point sampled. 16 quarters startup to compute initial HML factors. Model estimated on returns from 1977Q1 to 2014Q2. $\Delta y$, $y^{gap}$, $\Delta c$, $\Delta UE$, $UE^{gap}$, $\pi$, $q^{gap}$, and $\Delta q$ represent the GDP growth rate, output gap, consumption growth rate, change in the unemployment rate, unemployment gap, inflation rate, real exchange rate gap, and real exchange rate depreciation, respectively. For each country (41 countries plus the Euro area) and each macroeconomic variable ($x$), we compute the 'conditional' mean ($\mu_t(x)$), volatility ($\sigma_t(x)$) and skewness ($sk_t(x)$) using a 16-quarter window. To form the portfolio returns, we sort by the nominal interest rate (carry) for each country from low to high. The rank ordering is divided into six portfolios, into which the currency returns are assigned. $P_6$ is the portfolio of returns associated with the highest nominal interest rate countries and $P_1$ is the portfolio of returns associated with the lowest nominal interest rate countries. This table reports the two-pass procedure estimation results from a one-factor model. In the first pass, we run $N = 6$ individual time-series regressions of the excess returns on the $K$ factors to estimate the factor 'betas,' $r^e_{i,t} = a_i + \sum_{k=1}^{K} \beta_{i,k} f^{HML}_{k,t} + \epsilon_{i,t}$, where $r^e_{i,t}$ is the excess return, $\beta_{i,k}$ is the factor beta and $f^{HML}_{k,t}$ is the high-minus-low (HML) macro risk factor. The factors considered include the high-minus-low (HML) values of the conditional mean, variance, and skewness of $\Delta y$, $y^{gap}$, $\Delta c$, $\Delta UE$, $UE^{gap}$, $\pi$, $q^{gap}$, and $\Delta q$. Each HML value is equal to the average in the highest quartile minus the average in the lowest quartile. In the second pass, we run a single cross-sectional regression of the (time-series) mean excess returns on the estimated betas, $\bar{r}^e_i = \gamma + \sum_{k=1}^{K} \lambda_k \beta_{i,k} + \alpha_i$, where $\bar{r}^e_i$ is the average excess return, $\gamma$ is the intercept, $\lambda_k$ is the risk premia, and $\alpha_i$ is the pricing error. The table reports the price of risk ($\lambda$) and its associated t-ratio (using GMM standard errors), the estimated intercept ($\gamma$) and its associate t-ratio, $R^2$ and the Wald test on the pricing errors (Test-stat) and its associated p-value (p-val.). Bold indicates significance at the 5% level. '*' indicates significance at the 10% level.

Table 19: Two-Pass Estimation of the Two-Factor Beta-Risk Model on Carry Excess Returns, 1977Q1-2014Q2

| Two-Factor Model. First HML Factor is $sk_t(UE^{gap})$. | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $\lambda_1$ | t-ratio | $2^{nd}$ HML Factor | $\lambda_2$ | t-ratio | $\gamma$ | t-ratio | $R^2$ | Test-stat | p-val. |
| 0.406 | **1.988** | $sk_t(\Delta UE)$ | 0.752 | 1.664* | 3.209 | 0.853 | 0.996 | 0.097 | 1.000 |
| 0.524 | **2.982** | $sk_t(\Delta y)$ | 0.161 | 1.262 | 3.253 | 1.350 | 0.970 | 2.346 | 0.800 |
| 0.519 | **3.750** | $sk_t(y^{gap})$ | 0.156 | 1.065 | 2.712 | 0.969 | 0.972 | 2.301 | 0.806 |
| 0.490 | **2.836** | $sk_t(\Delta c)$ | 0.127 | 0.751 | 3.837 | 1.529 | 0.976 | 1.409 | 0.923 |
| 0.546 | **3.685** | $sk_t(\pi)$ | -0.156 | -1.217 | 4.269 | 1.460 | 0.984 | 0.845 | 0.974 |
| 0.456 | **2.884** | $sk_t(q^{gap})$ | 0.112 | 0.327 | 3.731 | 1.404 | 0.974 | 1.675 | 0.892 |
| 0.506 | **2.933** | $sk_t(\Delta q)$ | 0.312 | 1.382 | 3.638 | 1.445 | 0.972 | 2.231 | 0.816 |
| 0.413 | **3.005** | $\sigma_t(UE^{gap})$ | 0.354 | 0.342 | 3.527 | 1.560 | 0.976 | 2.863 | 0.721 |
| 0.481 | **3.434** | $\sigma_t(\Delta UE)$ | -0.013 | -0.300 | 3.198 | 1.305 | 0.966 | 3.038 | 0.694 |
| 0.351 | 1.708* | $\sigma_t(\Delta y)$ | 1.246 | 1.337 | 2.208 | 0.780 | 0.984 | 1.304 | 0.935 |
| 0.395 | **2.812** | $\sigma_t(y^{gap})$ | 0.548 | 1.811* | 2.494 | 0.912 | 0.995 | 0.528 | 0.991 |
| 0.430 | **2.917** | $\sigma_t(\Delta c)$ | 0.784 | 1.032 | 1.827 | 0.603 | 0.983 | 0.852 | 0.974 |
| 0.480 | **3.419** | $\sigma_t(\pi)$ | 2.158 | 1.818* | 2.985 | 1.284 | 0.969 | 2.878 | 0.719 |
| 0.487 | **3.520** | $\sigma_t(q^{gap})$ | 0.011 | 0.006 | 2.965 | 1.065 | 0.967 | 3.017 | 0.697 |
| 0.409 | **2.765** | $\sigma_t(\Delta q)$ | 4.963 | 1.454 | 3.294 | 1.480 | 0.974 | 2.918 | 0.713 |
| 0.445 | **3.325** | $\mu_t(UE^{gap})$ | 1.315 | 1.209 | 3.357 | 1.365 | 0.971 | 2.565 | 0.767 |
| 0.392 | **2.984** | $\mu_t(\Delta UE)$ | 0.039 | 1.497 | 3.311 | 1.203 | 0.986 | 0.964 | 0.965 |
| 0.422 | **1.966** | $\mu_t(\Delta y)$ | -1.366 | -1.579 | 2.826 | 1.038 | 0.977 | 1.105 | 0.954 |
| 0.489 | **2.777** | $\mu_t(y^{gap})$ | 0.312 | 1.051 | 3.268 | 1.379 | 0.974 | 2.276 | 0.810 |
| 0.316 | 0.945 | $\mu_t(\Delta c)$ | -1.388 | -1.285 | 1.468 | 0.376 | 0.987 | 0.509 | 0.992 |
| 0.467 | **2.953** | $\mu_t(\pi)$ | 5.232 | 1.791* | 3.102 | 1.394 | 0.968 | 2.924 | 0.712 |
| 0.499 | **3.671** | $\mu_t(q^{gap})$ | -0.159 | -0.323 | 3.240 | 1.171 | 0.990 | 0.432 | 0.994 |
| 0.484 | **3.502** | $\mu_t(\Delta q)$ | 0.948 | 0.733 | 2.915 | 1.053 | 0.967 | 3.227 | 0.665 |

Notes: The raw data are quarterly (1973Q1 to 2014Q2) and when available are end-of-quarter and point sampled. 16 quarters startup to compute initial HML factors. Model estimated on returns from 1977Q1 to 2014Q2. $\Delta y$, $y^{gap}$, $\Delta c$, $\Delta UE$, $UE^{gap}$, $\pi$, $q^{gap}$, and $\Delta q$ represent the GDP growth rate, output gap, consumption growth rate, change in the unemployment rate, unemployment gap, inflation rate, real exchange rate gap, and real exchange rate depreciation, respectively. For each country (41 countries plus the Euro area) and each macroeconomic variable ($x$), we compute the 'conditional' mean ($\mu_t(x)$), volatility ($\sigma_t(x)$) and skewness ($sk_t(x)$) using a 16-quarter window. To form the portfolio returns, we sort by the nominal interest rate (carry) for each country from low to high. The rank ordering is divided into six portfolios, into which the currency returns are assigned. $P_6$ is the portfolio of returns associated with the highest nominal interest rate countries and $P_1$ is the portfolio of returns associated with the lowest nominal interest rate countries. This table reports the two-pass procedure estimation results from a two-factor model where $sk_t(UE^{gap})$ is the maintained first factor. In the first pass, we run $N = 6$ individual time-series regressions of the excess returns on the $K$ factors to estimate the factor 'betas,' $r^e_{i,t} = a_i + \sum_{k=1}^{K} \beta_{i,k} f^{HML}_{k,t} + \epsilon_{i,t}$, where $r^e_{i,t}$ is the excess return, $\beta_{i,k}$ is the factor beta and $f^{HML}_{k,t}$ is the high-minus-low (HML) macro risk factor. The factors considered include the high-minus-low (HML) values of the conditional mean, variance, and skewness of $\Delta y$, $y^{gap}$, $\Delta c$, $\Delta UE$, $UE^{gap}$, $\pi$, $q^{gap}$, and $\Delta q$. Each HML value is equal to the average in the highest quartile minus the average in the lowest quartile. In the second pass, we run a single cross-sectional regression of the (time-series) mean excess returns on the estimated betas, $\bar{r}^e_i = \gamma + \sum_{k=1}^{K} \lambda_k \beta_{i,k} + \alpha_i$, where $\bar{r}^e_i$ is the average excess return, $\gamma$ is the intercept, $\lambda_k$ is the risk premia, and $\alpha_i$ is the pricing error. The table reports the price of risk ($\lambda$) and its associated t-ratio (using GMM standard errors), the estimated intercept ($\gamma$) and its associate t-ratio, $R^2$ and the Wald test on the pricing errors (Test-stat) and its associated p-value (p-val.). Bold indicates significance at the 5% level. '*' indicates significance at the 10% level.

Table 20: Two-Pass Estimation of the Single-Factor Beta-Risk Model on Carry Excess Returns, 1979Q1-2014Q2

| Single-Factor Model. | | | | | | | |
|---|---|---|---|---|---|---|---|
| HML Factor | $\lambda$ | t-ratio | $\gamma$ | t-ratio | $R^2$ | Test-stat | p-val. |
| $sk_t(UE^{gap})$ | 0.530 | **3.561** | 3.186 | 1.295 | 0.969 | 2.427 | 0.787 |
| $sk_t(\Delta UE)$ | 0.816 | **2.264** | 3.215 | 0.786 | 0.995 | 0.095 | 1.000 |
| $sk_t(\Delta y)$ | 0.427 | **2.580** | 5.480 | 1.930* | 0.677 | 5.141 | 0.399 |
| $sk_t(y^{gap})$ | 0.382 | **2.166** | 7.108 | **2.639** | 0.172 | 7.179 | 0.208 |
| $sk_t(\Delta c)$ | 0.592 | **2.317** | 7.672 | 1.990* | 0.630 | 2.513 | 0.775 |
| $sk_t(\pi)$ | -0.172 | -1.314 | 5.188 | **2.376** | 0.027 | 9.919 | 0.078 |
| $sk_t(q^{gap})$ | 0.876 | 1.797* | 6.720 | 1.679* | 0.250 | 3.823 | 0.575 |
| $sk_t(\Delta q)$ | 0.769 | **2.332** | 7.185 | **2.640** | 0.773 | 4.416 | 0.491 |
| $\sigma_t(UE^{gap})$ | 4.273 | **2.373** | 5.548 | 1.599 | 0.603 | 6.371 | 0.272 |
| $\sigma_t(\Delta UE)$ | 0.013 | 0.470 | 3.857 | **2.553** | 0.002 | 11.348 | 0.045 |
| $\sigma_t(\Delta y)$ | 2.093 | **2.737** | 1.216 | 0.341 | 0.967 | 1.117 | 0.953 |
| $\sigma_t(y^{gap})$ | 1.058 | **2.659** | 1.514 | 0.389 | 0.927 | 2.330 | 0.802 |
| $\sigma_t(\Delta c)$ | 2.079 | **2.386** | -1.326 | -0.282 | 0.890 | 1.730 | 0.885 |
| $\sigma_t(\pi)$ | 4.615 | **2.464** | 2.265 | 0.740 | 0.846 | 2.787 | 0.733 |
| $\sigma_t(q^{gap})$ | -6.824 | -1.203 | 5.959 | 1.031 | 0.320 | 1.951 | 0.856 |
| $\sigma_t(\Delta q)$ | 9.611 | **2.933** | 3.728 | 1.340 | 0.923 | 3.068 | 0.690 |
| $\mu_t(UE^{gap})$ | 4.242 | **2.718** | 4.632 | 1.065 | 0.818 | 3.330 | 0.649 |
| $\mu_t(\Delta UE)$ | 0.121 | **2.634** | 3.888 | 0.826 | 0.812 | 2.755 | 0.738 |
| $\mu_t(\Delta y)$ | -1.999 | **-2.465** | 2.496 | 0.718 | 0.970 | 0.635 | 0.986 |
| $\mu_t(y^{gap})$ | 0.981 | **2.788** | 3.840 | 1.011 | 0.796 | 3.096 | 0.685 |
| $\mu_t(\Delta c)$ | -1.453 | **-3.327** | 1.327 | 0.497 | 0.986 | 0.482 | 0.993 |
| $\mu_t(\pi)$ | 9.620 | **2.865** | 3.016 | 1.246 | 0.913 | 2.998 | 0.700 |
| $\mu_t(q^{gap})$ | 2.099 | **2.142** | 3.048 | 0.709 | 0.532 | 2.643 | 0.755 |
| $\mu_t(\Delta q)$ | 4.726 | 1.842* | -0.373 | -0.074 | 0.674 | 2.027 | 0.845 |

Notes: The raw data are quarterly (1973Q1 to 2014Q2) and when available are end-of-quarter and point sampled. 24 quarters startup to compute initial HML factors. Model estimated on returns from 1979Q1 to 2014Q2. $\Delta y$, $y^{gap}$, $\Delta c$, $\Delta UE$, $UE^{gap}$, $\pi$, $q^{gap}$, and $\Delta q$ represent the GDP growth rate, output gap, consumption growth rate, change in the unemployment rate, unemployment gap, inflation rate, real exchange rate gap, and real exchange rate depreciation, respectively. For each country (41 countries plus the Euro area) and each macroeconomic variable ($x$), we compute the 'conditional' mean ($\mu_t(x)$), volatility ($\sigma_t(x)$) and skewness ($sk_t(x)$) using a 24-quarter window. To form the portfolio returns, we sort by the nominal interest rate (carry) for each country from low to high. The rank ordering is divided into six portfolios, into which the currency returns are assigned. $P_6$ is the portfolio of returns associated with the highest nominal interest rate countries and $P_1$ is the portfolio of returns associated with the lowest nominal interest rate countries. This table reports the two-pass procedure estimation results from a one-factor model. In the first pass, we run $N = 6$ individual time-series regressions of the excess returns on the $K$ factors to estimate the factor 'betas,' $r^e_{i,t} = a_i + \sum_{k=1}^{K} \beta_{i,k} f^{HML}_{k,t} + \epsilon_{i,t}$, where $r^e_{i,t}$ is the excess return, $\beta_{i,k}$ is the factor beta and $f^{HML}_{k,t}$ is the high-minus-low (HML) macro risk factor. The factors considered include the high-minus-low (HML) values of the conditional mean, variance, and skewness of $\Delta y$, $y^{gap}$, $\Delta c$, $\Delta UE$, $UE^{gap}$, $\pi$, $q^{gap}$, and $\Delta q$. Each HML value is equal to the average in the highest quartile minus the average in the lowest quartile. In the second pass, we run a single cross-sectional regression of the (time-series) mean excess returns on the estimated betas, $\bar{r}^e_i = \gamma + \sum_{k=1}^{K} \lambda_k \beta_{i,k} + \alpha_i$, where $\bar{r}^e_i$ is the average excess return, $\gamma$ is the intercept, $\lambda_k$ is the risk premia, and $\alpha_i$ is the pricing error. The table reports the price of risk ($\lambda$) and its associated t-ratio (using GMM standard errors), the estimated intercept ($\gamma$) and its associate t-ratio, $R^2$ and the Wald test on the pricing errors (Test-stat) and its associated p-value (p-val.). Bold indicates significance at the 5% level. '*' indicates significance at the 10% level.

Table 21: Two-Pass Estimation of the Two-Factor Beta-Risk Model on Carry Excess Returns, 1979Q1-2014Q2

| | | Two-Factor Model. First HML Factor is $sk_t(UE^{gap})$. | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $\lambda_1$ | t-ratio | $2^{nd}$ HML Factor | $\lambda_2$ | t-ratio | $\gamma$ | t-ratio | $R^2$ | Test-stat | p-val. |
| 0.406 | **1.988** | $sk_t(\Delta UE)$ | 0.752 | 1.664* | 3.209 | 0.853 | 0.996 | 0.097 | 1.000 |
| 0.524 | **2.982** | $sk_t(\Delta y)$ | 0.161 | 1.262 | 3.253 | 1.350 | 0.970 | 2.346 | 0.800 |
| 0.519 | **3.750** | $sk_t(y^{gap})$ | 0.156 | 1.065 | 2.712 | 0.969 | 0.972 | 2.301 | 0.806 |
| 0.490 | **2.836** | $sk_t(\Delta c)$ | 0.127 | 0.751 | 3.837 | 1.529 | 0.976 | 1.409 | 0.923 |
| 0.546 | **3.685** | $sk_t(\pi)$ | -0.156 | -1.217 | 4.269 | 1.460 | 0.984 | 0.845 | 0.974 |
| 0.456 | **2.884** | $sk_t(q^{gap})$ | 0.112 | 0.327 | 3.731 | 1.404 | 0.974 | 1.675 | 0.892 |
| 0.506 | **2.933** | $sk_t(\Delta q)$ | 0.312 | 1.382 | 3.638 | 1.445 | 0.972 | 2.231 | 0.816 |
| 0.413 | **3.005** | $\sigma_t(UE^{gap})$ | 0.354 | 0.342 | 3.527 | 1.560 | 0.976 | 2.863 | 0.721 |
| 0.481 | **3.434** | $\sigma_t(\Delta UE)$ | -0.013 | -0.300 | 3.198 | 1.305 | 0.966 | 3.038 | 0.694 |
| 0.351 | 1.708* | $\sigma_t(\Delta y)$ | 1.246 | 1.337 | 2.208 | 0.780 | 0.984 | 1.304 | 0.935 |
| 0.395 | **2.812** | $\sigma_t(y^{gap})$ | 0.548 | 1.811* | 2.494 | 0.912 | 0.995 | 0.528 | 0.991 |
| 0.430 | **2.917** | $\sigma_t(\Delta c)$ | 0.784 | 1.032 | 1.827 | 0.603 | 0.983 | 0.852 | 0.974 |
| 0.480 | **3.419** | $\sigma_t(\pi)$ | 2.158 | 1.818* | 2.985 | 1.284 | 0.969 | 2.878 | 0.719 |
| 0.487 | **3.520** | $\sigma_t(q^{gap})$ | 0.011 | 0.006 | 2.965 | 1.065 | 0.967 | 3.017 | 0.697 |
| 0.409 | **2.765** | $\sigma_t(\Delta q)$ | 4.963 | 1.454 | 3.294 | 1.480 | 0.974 | 2.918 | 0.713 |
| 0.445 | **3.325** | $\mu_t(UE^{gap})$ | 1.315 | 1.209 | 3.357 | 1.365 | 0.971 | 2.565 | 0.767 |
| 0.392 | **2.984** | $\mu_t(\Delta UE)$ | 0.039 | 1.497 | 3.311 | 1.203 | 0.986 | 0.964 | 0.965 |
| 0.422 | **1.966** | $\mu_t(\Delta y)$ | -1.366 | -1.579 | 2.826 | 1.038 | 0.977 | 1.105 | 0.954 |
| 0.489 | **2.777** | $\mu_t(y^{gap})$ | 0.312 | 1.051 | 3.268 | 1.379 | 0.974 | 2.276 | 0.810 |
| 0.316 | 0.945 | $\mu_t(\Delta c)$ | -1.388 | -1.285 | 1.468 | 0.376 | 0.987 | 0.509 | 0.992 |
| 0.467 | **2.953** | $\mu_t(\pi)$ | 5.232 | 1.791 | 3.102 | 1.394 | 0.968 | 2.924 | 0.712 |
| 0.499 | **3.671** | $\mu_t(q^{gap})$ | -0.159 | -0.323 | 3.240 | 1.171 | 0.990 | 0.432 | 0.994 |
| 0.484 | **3.502** | $\mu_t(\Delta q)$ | 0.948 | 0.733 | 2.915 | 1.053 | 0.967 | 3.227 | 0.665 |

Notes: The raw data are quarterly (1973Q1 to 2014Q2) and when available are end-of-quarter and point sampled. 24 quarters startup to compute initial HML factors. Model estimated on returns from 1979Q1 to 2014Q2. $\Delta y$, $y^{gap}$, $\Delta c$, $\Delta UE$, $UE^{gap}$, $\pi$, $q^{gap}$, and $\Delta q$ represent the GDP growth rate, output gap, consumption growth rate, change in the unemployment rate, unemployment gap, inflation rate, real exchange rate gap, and real exchange rate depreciation, respectively. For each country (41 countries plus the Euro area) and each macroeconomic variable ($x$), we compute the 'conditional' mean ($\mu_t(x)$), volatility ($\sigma_t(x)$) and skewness ($sk_t(x)$) using a 24-quarter window. To form the portfolio returns, we sort by the nominal interest rate (carry) for each country from low to high. The rank ordering is divided into six portfolios, into which the currency returns are assigned. $P_6$ is the portfolio of returns associated with the highest nominal interest rate countries and $P_1$ is the portfolio of returns associated with the lowest nominal interest rate countries. This table reports the two-pass procedure estimation results from a two-factor model where $sk_t(UE^{gap})$ is the maintained first factor. In the first pass, we run $N = 6$ individual time-series regressions of the excess returns on the $K$ factors to estimate the factor 'betas,' $r^e_{i,t} = a_i + \sum_{k=1}^{K} \beta_{i,k} f^{HML}_{k,t} + \epsilon_{i,t}$, where $r^e_{i,t}$ is the excess return, $\beta_{i,k}$ is the factor beta and $f^{HML}_{k,t}$ is the high-minus-low (HML) macro risk factor. The factors considered include the high-minus-low (HML) values of the conditional mean, variance, and skewness of $\Delta y$, $y^{gap}$, $\Delta c$, $\Delta UE$, $UE^{gap}$, $\pi$, $q^{gap}$, and $\Delta q$. Each HML value is equal to the average in the highest quartile minus the average in the lowest quartile. In the second pass, we run a single cross-sectional regression of the (time-series) mean excess returns on the estimated betas, $\bar{r}^e_i = \gamma + \sum_{k=1}^{K} \lambda_k \beta_{i,k} + \alpha_i$, where $\bar{r}^e_i$ is the average excess return, $\gamma$ is the intercept, $\lambda_k$ is the risk premia, and $\alpha_i$ is the pricing error. The table reports the price of risk ($\lambda$) and its associated t-ratio (using GMM standard errors), the estimated intercept ($\gamma$) and its associate t-ratio, $R^2$ and the Wald test on the pricing errors (Test-stat) and its associated p-value (p-val.). Bold indicates significance at the 5% level. '*' indicates significance at the 10% level.