# The Mystery of Currency Betas

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**Abstract**

Currencies are heterogeneously exposed to global risk. But the reason why remains a mystery. A theoretical explanation should identify the source of asymmetry between countries and hence, explain why beta – the loading on global risk – varies across currencies. In this paper, I first test leading theoretical explanations for the root of the asymmetry and find only the time-varying 'surplus-consumption' prediction of Verdelhan (2010) to be supported. When I go on to consider alternative, 'characteristic' factors, I find a country's current account and 'investment profile' provide incremental information on the variation in currency betas. The results shed light on the macroeconomic drivers of conditional and unconditional carry returns, while highlighting the importance of focusing on risk *exposure* in theoretical models of currency premia and on imposing statistical restrictions in empirical tests of currency factors.

*Keywords:* Currency premia, consumption-based asset pricing, cross-sectional tests, forward premium puzzle.

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# 1 Introduction

An investor who enters a 'carry trade' – simultaneously lending in high-interest-rate currencies and borrowing in low-interest-rate currencies – will, on average, make a profit. This is perhaps the most widely cited puzzle in international finance and a result often attributed as compensation for bearing risk (Hansen and Hodrick, 1980; Fama, 1984; Lustig and Verdelhan, 2007).[1] Indeed, Lustig, Roussanov, and Verdelhan (2011) document that a single, 'global' (systematic) risk factor can account for the cross-section of carry trade returns. Currencies with high interest rates are positively exposed to global risk (highest currency beta), while low-interest-rate currencies are negatively exposed (lowest currency beta). Yet, the risk-based explanation raises a fundamental question: *why* are high-interest-rate currencies the riskiest? In other words, what is the fundamental macroeconomic rationale for why some currencies are expected to earn a higher return and hence, from a risk perspective, be more likely to depreciate during 'bad times'?

Recent empirical studies have replaced the global factor in Lustig et al. (2011) with alternative factors, constructed to provide deeper insight into the underlying risk to which carry trade investors are exposed. Candidate risks include innovations in currency volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012), skewness (Rafferty, 2012) and correlation (Mueller, Stathopoulos, and Vedolin, 2013), while a related literature focuses on a 'downside' risk version of the Capital Asset Pricing Model (CAPM), in which high-interest-rate currencies are found to have the largest sensitivity to negative equity returns (Dobrynskaya, 2014; Galsband and Nitschka, 2013; Lettau, Maggiori, and Weber, 2014).[2] These alternative factors, however, remain silent as to *why* some currencies (and not others) depreciate when risk is high. That is, they concentrate on the price and not the quantity (beta) of risk.

Understanding the source of the variation in betas is important. It is well known to currency and risk managers that high-interest-rate currencies have a higher expected return.[3] Yet the

[1]Other early work in this area includes Tryon (1979) and Bilson (1981). Useful surveys of the literature include Froot and Thaler (1990), Lewis (1995) and Engel (1996), while Koijen, Moskowitz, Pedersen, and Vrugt (2013) provide recent empirical evidence across assets. Other explanations exist in the literature for why high-interest-rate currencies earn a high expected return. These include, among others, 'peso' problems (Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011a), funding liquidity spirals (Brunnermeier, Nagel, and Pedersen, 2008; Gabaix and Maggiori, 2014), overconfidence (Burnside, Han, Hirshleifer, and Wang, 2011b) and adverse selection problems within the foreign exchange market (Burnside, Eichenbaum, and Rebelo, 2009).

[2]The surge in newly proposed currency factors echoes developments in the equity market literature, which is characterized by, and criticized for, an ever expanding array of new risk factors (Harvey, Liu, and Zhu, 2013). In fact, this phenomenon has generated a growing literature critical of standard empirical asset pricing tests, which show that many equity factors may only have a spurious relationship with equity portfolio returns (Kan, Robotti, and Shanken, 2013), have little correlation with other proposed factors (Daniel and Titman, 2012) or be 'priced' due to the low statistical power of the asset pricing test (Lewellen, Nagel, and Shanken, 2010).

[3]In fact, the carry trade has been found to be the most popular quantitative strategy in the foreign exchange

underlying macroeconomic explanation remains a mystery. If the fundamental source of exposure to risk is stable relative to interest rates, then a strategy which loads positively on the exposure could generate higher returns, lower volatility and smaller transaction costs relative to the standard carry trade. If so, currency managers can adapt to fluctuations in the investment opportunity set in a more timely and efficient manner. Furthermore, by deepening our understanding of why some currencies are more (or less) exposed to common shocks and hence, why betas differ across currencies, we may garner richer insights into the fundamental drivers of macroeconomic risk itself.

The literature on the foreign exchange market is not short of possible explanations for why betas vary across currencies. In fact, a recent surge in the modeling of currency risk premia has generated several alternative and competing implications for the fundamental source of currency risk exposure. The only necessary common feature among these models is that they identify a source of asymmetry between countries which generates the risk premia.[4] But these theoretical implications are rarely highlighted and have not been empirically scrutinized in the literature. In this paper, I investigate a leading set of recently developed theoretical models of currency premia, by putting each of the models' implications regarding the source of currency betas under the microscope. In particular, I focus on the external-habit model of Verdelhan (2010), the long-run risks model of Colacito and Croce (2013) and the variable rare disasters models of Farhi and Gabaix (2014).[5]

Sorting currencies based on the model-implied source of riskiness should yield a cross-section of portfolio returns. Moreover, from these portfolio returns, a factor should be constructible which can proxy for global risk, explain the cross-section of carry trade returns and hence, provide information on the source of currency risk exposure. Investigating theoretical models using a risk factor/cross-sectional approach, provides a framework for testing – in a unified manner – the higher level predictions of leading theoretical models, while also avoiding the numerous issues surrounding badly measured aggregate consumption data and imprecise estimation of parameterized models.[6]

market (Galati, Heath, and McGuire, 2007; Rime and Schrimpf).

[4]Lustig et al. (2011) and Hassan and Mano (2014) provide further details on the necessity for models of currency premia to incorporate *asymmetric* countries, which interact in international financial markets.

[5]The test group of models reflect the main branches, or variations, of the consumption-based model in use today and represent an analogous group of models to those investigated in an equity market setting by Van Binsbergen, Brandt, and Koijen (2012). In their paper, the authors focus on the habit preferences model of Campbell and Cochrane (1999), the long-run risks model of Bansal and Yaron (2004) and the variable rare disaster model of Gabaix (2012) which builds on the earlier work of Rietz (1988) and Barro (2006).

[6]A recent debate in the literature has cast doubts on the consumption-based model's ability to explain currency excess returns. Lustig and Verdelhan (2007) showed that currency risk premia are compensation for bearing aggregate U.S. consumption risk. The claim was, however, countered by Burnside (2011), who raised a series of

In the empirical analysis, I begin by documenting the relative ease in explaining the variation in returns to interest-rate sorted portfolios. Artificially simulated risk factors are overwhelmingly found to exhibit high t-statistics and impressive model goodness-of-fit. I find the same pattern when using real country-risk data from the Political Risk Services (PRS) Group. To resolve the issue of low statistical power, I impose the restrictions suggested by Lewellen, Nagel, and Shanken (2010), and demonstrate the improvement, including only 5% of randomly constructed factors now exhibiting a t-statistic in excess of two. Taking this approach to the theoretically motivated factors I find, in general, they cannot explain any of the cross-section of carry trade returns. In standard cross-sectional asset pricing tests, models generate near-zero or negative cross-sectional *adj-*$R^2$ and large root-mean-squared pricing errors. Pertinently, I find most factors are not statistically significant, nor do they exhibit a high correlation with the 'true' global risk in currency markets.

In some instances, the factor price of risk is significant but *negative*, suggesting the model's predictions work in the opposite direction to the data. Only the 'surplus-consumption' prediction of Verdelhan (2010), based on an external-habit utility framework, is found to be supported in the data. The factor, constructed on the basis of countries' output gap, is found to be statistically significant in cross-sectional tests. It generates the well-known 'slope' of beta coefficients in time-series regressions, and explains up to 50% of the variation in expected currency excess returns. The factor captures the risk of investing in countries operating above long-run capacity, in which current investment returns and real interest rates are above their long-run level.

The spread in excess returns to surplus-consumption-sorted portfolios is, however, only around 40% of that for forward-premia sorted portfolios. To build on the findings, I investigate if other 'characteristic-based' factors can provide incremental information as to why currencies exhibit heterogenous exposure to risk. To do so, I again use data from the Political Risk Services (PRS) Group to construct 25 alternative characteristic factors based on country-level macroeconomic, financial and political risks. The majority of factors are rejected in standard cross-sectional tests, but a common trend emerges: macroeconomic-based risks *are* priced. That is, risks associated with the level of a country's borrowing (both sovereign and external), its investment risks (FX volatility, contract viability, profit repatriation) and socioeconomic conditions (GDP per capita,

issues with the underlying methods and interpretation of the results. This critique prompted a defence of the techniques used and their application in the original study (Lustig and Verdelhan, 2011). Ready, Roussanov, and Ward (2013) also propose a consumption-based model for the unconditional carry trade, highlighting that variations in currency risk are determined by asymmetric shipping costs over the business cycle, making commodity countries the riskiest. The authors also construct portfolios sorted on the basis of the risk exposure but, unlike this study, do not perform cross-sectional asset pricing tests.

unemployment, consumer confidence) are all found to be priced risk factors.

These findings are consistent with an earlier literature on the determinants of real-interest rates (Howe and Pigott, 1992; Orr, Edey, and Kennedy, 1995), which finds countries with high investment returns – and large risks to those investment returns – are the most important determinants of real rates. Indeed, the authors find that saving-investment imbalances and rising sovereign debt ratios are particularly important. This link between the literatures on real rates and currency premia follows from the empirical observation that relative Purchasing Power Parity (PPP) (the theory that exchange rate returns over time equal cross-country inflation differentials), holds in the long run (Taylor and Taylor, 2004). It thus follows that real-interest-rate differentials are the primary component of carry trade returns (see Section 2 for full details).

Overall, the results cast doubt on the ability of leading theoretical models of currency premia to explain why some currencies are more exposed to global risk than others. Employing a cross-sectional asset pricing approach can tease out which theoretical predictions, on the determination of real-interest-rates and currency premia, are supported in the data. The information is important for casting light on the risks to which carry traders are exposed, i.e. on the determinants of currency betas. The findings suggest countries offering the carry trader the highest return and risk are operating above economic capacity, offering currently high returns but with growing investment risks, from increased internal and external borrowing. Moreover, the dynamic (output gap) and static (borrowing, investment risks) elements of the identified characteristics, are also consistent with the conditional and unconditional components of the currency carry trade, offering guidance for future theoretical and empirical work seeking to provide a more complete description of both the price and quantity of currency risk.

The remainder of the paper is organized as follows: in Section 2, I present the background to the investigation and describe the empirical methods to be used. In Section 3, I provide details of the data and factor construction. In Section 4, I investigate the statistical power of empirical asset pricing tests with commonly used currency portfolio test assets. In Section 5, I present results for the theoretically motivated factors. I investigate alternative characteristic factors in Section 6. I conclude in Section 7. In the Online Appendix, I provide further robustness tests and additional supporting analysis.

# 2 Background and Empirical Methodology

## 2.1 Currency risk and real interest rates

Positive returns to the currency carry trade reflect a failure of Uncovered Interest Parity (UIP), the benchmark model of foreign exchange rate behavior. According to UIP, an investor seeking to profit from cross-country interest-rate differentials will be unsuccessful due to, *on average*, the high-interest-rate currency depreciating to exactly offset the interest-rate differential. If this relationship holds, the forward premium would act as an unbiased predictor of future exchange rate movements.[7] The forward premium is, however, uncorrelated with spot exchange rate changes ($R^2 \approx 0$), a phenomenon referred to as the "forward premium puzzle". The puzzle is synonymous with the empirical failure of UIP and positive carry trade returns.

To better understand the nature of carry returns, Lustig, Roussanov, and Verdelhan (2011) construct a set of currency portfolios sorted by interest rates, and find that a single 'global' risk factor can explain those returns.[8] The portfolios themselves are found to exhibit a strong factor structure, with two principal components explaining around 90% of variation in returns. The authors use this finding to construct two risk factors which correlate highly with the first two principal components, in an application of the Arbitrage Pricing Theory of Ross (1976). The first risk factor is constructed as an equally weighted average of currency portfolio returns and is denoted *Dollar* risk (*DOL*) but has no cross-sectional pricing power.[9] The second risk factor is denoted *Slope* risk and is constructed as a 'high-minus-low' (HML) factor, by taking the difference in returns on the extreme portfolios.

*Slope* risk explains all of the heterogeneity in currency risk exposure, with high-interest-rate currencies found to be the most exposed to the global risk. In fact, *Slope* risk correlates almost perfectly with the second principal component, and thus could be viewed as a proxy for the 'true' underlying risk factor.[10] The authors argue that to rationalize this finding requires countries to exhibit significant heterogeneity in their beta loading on global risk, although remain silent on the nature of the asymmetry across countries.

[7]This relationship follows from Covered Interest Parity (CIP), a no-arbitrage condition linking forward and spot exchange rates by the interest-rate differential.

[8]More precisely, the authors sort currencies according to their forward premia – a technique pioneered by Lustig and Verdelhan (2007). Under no-arbitrage conditions, however, sorting on forward premia is equivalent to sorting on interest rates, and hence the portfolios range from the lowest to the highest-interest-rate currencies.

[9]The factor effectively works as a constant in the model. Some recent papers, however, including Verdelhan (2013) and Maggiori (2013), have given more support to *DOL* risk being an economically important factor.

[10]Similarly, Lewellen et al. (2010) argue that the *HML* and *SMB* risk factors proposed by Fama and French (1993) are good proxies for the 'true' underlying risk factors when pricing book-to-market and size-sorted portfolios, due to their high correlation with the main principal components of those portfolio returns.

**Persistent asymmetric risk exposure.** On the topic of the forward premium puzzle, Cochrane (2005) notes that "the puzzle does *not* say that one earns more by holding bonds from countries with higher interest rates than others... the puzzle *does* say that one earns more by holding bonds from countries whose interest rates are *higher than usual* relative to U.S. interest rates". In this case we would expect currencies with on average high interest rates, such as the Turkish lira or Brazilian real, to be unprofitable investments for a carry-trade investor. Yet this is not the case. The 'static' or 'unconditional' carry trade, which involves sorting currencies into portfolios, based on average historical interest rates at time-$t$, and then holding the portfolios in perpetuity without rebalancing, yields sizeable profits. Hassan and Mano (2014) find the static carry trade accounts, in some instances, for over 100% of carry trade returns, while Lustig et al. (2011) find the unconditional trade accounts for around 80% of developed country carry returns and 50% when including emerging economy currencies. Two components thus make up the asymmetry in risk exposure. The first is a highly persistent unconditional (country-specific) exposure, while the second is dynamic conditional exposure which changes the relative ordering of risk across countries over time.

**Asymmetric risk and the real economy.** It should also be noted that the source of risk is, predominately, a real-interest rate phenomenon – rather than simply being a function of monetary/inflationary pressures. To see this, note that according to UIP the expected change in the spot exchange rate between time-$t$ and $t+1$ is defined as

$$E_t[\Delta s_{t+1}] = \Delta s_{t+1} + \eta_{t+1} = i_t - i_t^*, \tag{1}$$

where $\eta_{t+1}$ is a zero-mean (by assumption) ex-post error in expectations, $\Delta s_{t+1}$ is the change in the log spot exchange rate (denoted as number of home currency units per foreign currency unit), while $i_t$ and $i_{t+1}^*$ denote the risk-free home and foreign interest rates on a one-period bond. Furthermore, note that the real-interest rates in the home and foreign economies are given by

$$r_t = i_t - E_t[\pi_{t+1}] \qquad \text{and} \qquad r_t^* = i_t^* - E_t[\pi_{t+1}^*], \tag{2}$$

where $E_t[\pi_{t+1}]$ is the expected rate of inflation over one period. The ex-post realized rate of inflation can then be decomposed between the ex-ante expected rate of return and an ex-post error in expectations

$$\pi_{t+1} = E_t[\pi_{t+1}] + \epsilon_{t+1} \qquad \text{and} \qquad \pi^*_{t+1} = E_t[\pi^*_{t+1}] + \epsilon^*_{t+1}. \tag{3}$$

By combining equations (2) and (3), the interest rate differential between the home and foreign countries can thus be rewritten as

$$i_t - i^*_t = (r_t - r^*_t) + (\pi_{t+1} - \pi^*_{t+1}) - (\epsilon_{t+1} - \epsilon^*_{t+1}). \tag{4}$$

According to relative Purchasing Power Parity (PPP), the spot exchange rate should adjust to fluctuations in the relative inflation differential between two countries, such that high relative inflation results in a currency depreciation, i.e., $\Delta s_{t+1} = \pi_{t+1} - \pi^*_{t+1}$. Taylor and Taylor (2004) show that the parity condition holds over long periods. In the cross-section, the average inflation differential between a given country and the U.S. is equal to the average spot exchange rate return against the U.S. dollar ($E[\Delta s_{t+1}] = E_t[\pi_{t+1}] - E_t[\pi^*_{t+1}]$), which is consistent with high-interest rate countries *depreciating* on average, rather than *appreciating*, as is commonly interpreted from Fama (1984) regressions. When this cross-section is plotted, each point lies approximately on the $45^o$ ray with the $R^2 \approx 100\%$. It therefore follows that the currency risk premia $\lambda$, where $\lambda = (i_t - i^*_t) - E_t[\Delta s_{t+1}]$, can be simplified by substituting (4) into (1) and assuming both relative PPP holds *on average* and investors form rational expectations, such that

$$\lambda = r_t - r^*_t, \tag{5}$$

which implies that differences in *real* interest rates help account for the currency carry trade.

Indeed, it is widely known that real interest rates differ significantly around the world. Mishkin (1984), for example, provides an early study on the variation in international real rates. It thus follows that carry-trade investors are compensated for investing in countries with persistently high (above world level) real rates of interest, and hence the source of underlying risk exposure (measured as the currency beta) should be linked to *why* some countries offer consistently high real interest rates. If all countries, on average, offered the same real interest rate (as assumed by some standard open-economy macroeconomic models), then the earlier statement of Cochrane (2005) would hold – only short-run deviations from a country's *average* real rate of interest (the world rate) would generate a premium.[11]

[11] The link between real interest rates and carry returns has been documented in the empirical literature. Lustig et al. (2011), for example, find that the average excess return to high-interest-rate currencies is 3.38% (annualized) compared to a real interest rate differential of 3.78%. For low-interest-rate currencies the excess return of -1.17% is also comparable to the -1.81% real interest rate differential. The same pattern holds for developed countries

**Testing theoretical models of beta asymmetry.** General equilibrium models of currency premia offer precise explanations for the asymmetry in real interest rates across countries, and hence, for the variation in currency betas observed in the data. The models may work to capture either the persistent unconditional risk or conditional fast moving component. The empirical method adopted by Lustig et al. (2011) provides an ideal tool for testing these theories of beta variation. If a theoretical model performs well in capturing both conditional and unconditional components, then sorting currencies based on the model's implied source of risk exposure, should generate a spread in returns not dissimilar from sorting currencies by interest rates. A proxy for the 'global' factor, which captures the theory's prediction on the underlying source of risk, can be constructed to replace *Slope* risk and, crucially, be tested for statistical significance using standard empirical asset pricing techniques. Even if the model is only designed to capture either the conditional or unconditional component, the returns should still form a monotonic spread – just of lower magnitude relative to the standard carry trade.

## 2.2 Hypotheses

If a theoretically motivated factor can explain variation in betas, we would expect to make two empirical observations:

1. The excess return to the 'riskiest' portfolio should be greater than the 'safest'. Moreover, returns should increase monotonically from the 'safest' to 'riskiest' portfolios.
2. A return-based risk factor, constructed as the difference in returns between the 'riskiest' and 'safest' currencies should explain variation in expected carry-trade returns.

The first observation simply reflects that riskier assets should command higher returns – consistent with the risk-based view of carry-trade returns. The second observation follows from the empirical finding that *Slope* risk can explain carry-trade returns. Factors which provide a deeper economic insight into the success of *Slope* risk should, therefore, perform similarly well in explaining the returns to the carry trade.

## 2.3 Cross-Sectional Empirical Asset Pricing

In this section, I briefly outline the empirical asset pricing tests to be used in evaluating theoretically-motivated 'global' factors.

(3.07% vs 3.01% for high yielding currencies and -0.02% vs -1.11% for low yielding currencies). Differences in the figures could partly be reflected by the overly conservative transaction costs employed by Lustig et al. (2011). See Darvas (2009) for a discussion on incorporating foreign exchange rollover costs in empirical work.

**Methods.** I follow standard notation and denote the discrete excess return on currency portfolio $j$ in period $t$ as $RX_t^j$. In the absence of arbitrage opportunities, risk-adjusted excess returns have a price of zero and satisfy the following Euler equation:

$$E_t[M_{t+1}RX_{t+1}^j] = 0 \tag{6}$$

with a Stochastic Discount Factor (SDF) $M_{t+1}$, modeled as a linear function of the pricing factors $f_{t+1}$, given by

$$M_{t+1} = 1 - b'\left(f_{t+1} - \mu\right) \tag{7}$$

where $b$ is the vector of factor loadings, and $\mu$ denotes the factor means. This specification implies a beta pricing model where the expected excess return on portfolio $j$ is equal to the factor price of risk $\lambda$, times the quantity of risk $\beta^j$, such that

$$E[RX^j] = \lambda'\beta^j \tag{8}$$

where the market price of risk $\lambda = \Sigma_f b$ can be obtained via the factor loadings $b$.[12] $\Sigma_f = E\left[\left(f_t - \mu\right)\left(f_t - \mu\right)'\right]$ is the variance-covariance matrix of the risk factors, and $\beta^j$ are the regression coefficients of each portfolio's excess return $RX_{t+1}^j$ on the risk factors $f_{t+1}$.

The factor loadings $b$ entering equation (7) and risk prices $\lambda$ entering equation (8) are estimated via the Generalized Method of Moments ($GMM$) of Hansen (1982). To implement $GMM$, I use the pricing errors as a set of moments and a prespecified weighting matrix. Since the objective is to test whether the model can explain the cross-section of expected currency excess returns, I only rely on unconditional moments and do not employ instruments other than a constant and a vector of ones. The first-stage estimation ($GMM_1$) employs an identity weighting matrix. The weighting matrix tells us how much attention to pay to each moment condition. With an identity matrix, $GMM$ attempts to price all currency portfolios equally well.

The second-stage estimation ($GMM_2$) uses an optimal weighting matrix based on a heteroskedasticity and autocorrelation consistent (HAC) estimate of the long-run covariance matrix of the moment conditions. In this case, since currency portfolio returns have different variances and may be correlated, the optimal weighting matrix will attach more weight to linear combinations of moments about which the data are more informative (Cochrane, 2005). The tables report estimates of $b$ and $\lambda$ as well as standard errors based on Newey and West (1987). The model's performance is then evaluated using the cross-sectional $R^2$, the square-root of mean-squared pricing

[12] See Cochrane (2005) pp. 100-101, for full details.

errors $RMSPE$, and the $\chi^2$ test statistics. The $\chi^2$ test statistic evaluates the null hypothesis that all cross-sectional pricing errors (i.e., the difference between actual and predicted excess returns) are jointly equal to zero. Asymptotic $p$-values are reported for the $\chi^2$ test statistics.

The estimation of the portfolio betas $\beta^j$ and factor price of risk $\lambda$ in equation (8) is also undertaken using a two-pass ordinary least squares regression following Fama and MacBeth (FMB, 1973). In the first step, portfolio excess returns are regressed against a constant, $DOL$ risk, and the characteristic-based risk factor for each test-asset portfolio, after which I collect estimates of the time-series betas $\beta^j$. In the second step, a series of cross-sectional regressions are estimated in which portfolio returns, at each point in time, are regressed on the currency betas estimated in the first-stage time series regressions. The factor prices of risk $\lambda$, are then calculated by taking the average across all the estimated slope coefficients.[13] Standard errors are corrected according to Shanken (1992) with optimal lag length set according to Newey and West (1987).

# 3 Data and Portfolio Construction

## 3.1 Foreign Exchange Rates

**Foreign exchange data.** Following Della Corte, Riddiough, and Sarno (2014), I use monthly forward and spot exchange rates for 55 currencies collected from Barclays and Reuters via Datastream. All exchange rates are quoted against the U.S. dollar (USD) and the sample period is from October 1983 to December 2011. The countries include: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Egypt, Estonia, Euro Area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, Ukraine, United Kingdom, and Venezuela. I refer to this sample as *All Countries*.

As a robustness check, I also examine a smaller *Developed Countries* sample. The sample comprises the most liquidly traded currencies in the market, including: Australia, Belgium, Canada, Denmark, Euro Area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. After the introduction of the euro in January 1999, the Eurozone countries are replaced with the euro.

[13] Note that no constant is included in the second stage of the *FMB* regressions. The results would remain virtually identical however, if the *DOL* factor was replaced with a constant, as it effectively substitutes into the model as a common mispricing term.

**Computing Currency Excess Returns.** I denote time-$t$, spot and forward exchange rates as $S_t$ and $F_t$, respectively. Exchange rates are defined in units of foreign currency per U.S. dollar such that an increase in $S_t$ is an appreciation of the dollar. The excess return on buying a foreign currency in the forward market at time $t$ and then selling it in the spot market at time $t+1$ is computed as

$$RX_{t+1} = \left(F_t - S_{t+1}\right)/S_t, \tag{9}$$

which is equivalent to the forward premium minus the spot exchange rate return $RX_{t+1} = \left(F_t - S_t\right)/S_t - \left(S_{t+1} - S_t\right)/S_t$. According to the CIP condition, the forward premium approximately equals the interest rate differential $\left(F_t - S_t\right)/S_t \simeq i_t^* - i_t$, where $i_t$ and $i_t^*$ represent the domestic and foreign risk-free rates over the maturity of the forward contract. Since CIP holds closely in the data at daily and lower frequencies (Akram, Rime, and Sarno, 2008), the currency excess return is approximately equal to the interest rate differential minus the exchange rate return

$$RX_{t+1} \simeq i_t^* - i_t - \left(S_{t+1} - S_t\right)/S_t. \tag{10}$$

**Test Asset Portfolios.** Test asset portfolios are formed by sorting currencies each month based on their forward premia relative to the US dollar. High forward-premia currencies are those with the highest interest rate and are placed in the fifth portfolio, while low interest currencies are placed in the first portfolio. The Slope factor of Lustig et al. (2011) is constructed by taking the difference in returns on the fifth and first portfolios, while the $DOL$ factor is constructed by taking the average return across all five portfolios. Full details on the formation of the test portfolios can be found in Della Corte, Riddiough, and Sarno (2014).

## 3.2 Theoretically-Motivated Factors

### 3.2.1 Factor Construction

In this section, I describe how I empirically capture the 'beta predictions' of the theoretical models of currency premia, by sorting currencies into portfolios and forming macroeconomic factors to be used in empirical asset pricing tests.

## 3.3 Resilience to World Disasters

**Summary of the model.** Farhi and Gabaix (2014) construct a variable rare disasters model in which the 'resilience' of a country explains its exposure to common shocks. Resilience is measured by how well a country's economic activity (described as 'productivity' within the model) is insulated from rare world disasters – a disaster being an occasion when marginal utility is high and economic activity falls considerably. All countries are affected by the rare event but some countries, whose productivity falls significantly during disasters, are more exposed to the risk than others and thus riskier. The asymmetry across countries is captured within the model by the resilience variable $H$, which is defined as

$$H_{it} = p_{it}\mathbb{E}_t^{ND}[B_{t+1}^{-\gamma}F_{it+1} - 1] \tag{11}$$

where $H_{it}$ is the resilience of county $i$ at time $t$, $p_t$ is the probability of the disaster taking place and is multiplied by the expected value conditional on a disaster taking place at $t+1$, where the value is given by the discounted growth in productivity between $t$ and $t+1$ (pricing kernel $B_{t+1}^{-\gamma}$ times productivity growth $F_{i,t+1}$). All countries' pricing kernels evolve symmetrically, hence the differentiating factor is $F$. If $F_{i,t+1} = 0.8$ then productivity (economic activity) falls by 20% in country $i$, when the disaster occurs. It thus follows that the lower $H$ is, the less resilient and riskier the country.

Less resilient countries have the highest real interest rates and the largest expected currency premia. The excess return to the carry trade can be shown to equal the difference in resilience levels between two countries (Proposition 5 in Farhi and Gabaix (2014)),

$$\lambda = (i_t - i_t^*) - E_t^{ND}[\Delta s_{t+1}] = H_t^* - H_t \tag{12}$$

where $E_t^{ND}$ is the expectation conditional on there being no disaster in $t+1$.

**How the prediction is empirically tested.** The authors link the probability of a disaster with option market prices. If put options are expensive, relative to call options (i.e. the absolute value of the risk reversal is high), it indicates that there is a higher relative likelihood of the currency being subject to a large depreciation. The authors link the put premium to $H$ and hence, the riskiest countries are associated with the most expensive risk reversals, and should therefore experience a larger depreciation in bad times. The argument is consistent with a number of recent papers which link the probability of a 'crash' with currency risk premia (Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011a; Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan, 2013; Jurek, 2014). While the link between risk reversals and currency premia has now been widely documented, what remains unexamined is the link between a country's resilience to world economic disasters and the level of the risk reversal. Is it the case that countries with the largest crash exposure, also experience the largest fall in *economic activity* following the disaster? If not, then it could still be the case that currency premia reflect (at least in part) an underlying 'crash premium' but the macroeconomic explanation linking risk to exposure, would remain unexplained.

**Capturing the exposure to risk.** The extent to which a country is insulated from a global disaster can be empirically captured by its dependence on exports. A recent United Nations (2011) report notes that "[i]t is widely acknowledged that an economy's vulnerability to exogenous economic shocks is largely determined by its degree of exposure to the global economy."[14] – the rationale being that economies which are highly dependent on exports are vulnerable to external economic shocks, because the income from exports is generally used to finance imports, while also contributing directly to investment and growth.[15]

Export exposure is not, however, the only important factor in explaining exposure to large economic falls in activity. As emphasized in the same United Nations (2011) report, a second factor is export *concentration*. Some countries, which may be largely reliant on exports, such as Singapore or Hong Kong may, in fact, be relatively well insulated from world disasters because their export mix is highly diversified, either in terms of product mix or consumer (country) mix. Yet it is not clear if a more diversified product or market mix is always a clear sign of a more resilient country. Cadot, Carrère, and Strauss-Kahn (2011) find that export diversification exhibits a 'hump' shape – low in both the least developed and most developed countries. In essence, countries increase their specialization as they become more advanced, rather than offering a supermarket of products – potentially increasing their product margin and resilience to world economic downturns.

In Figure 1, I examine the relationship between economic dependence and the fall in economic activity during a global economic disaster. The global financial crisis of 2007-2009 provides an

[14] In the popular press, Singapore "is often seen as a barometer of world demand because its economy...is one of the most export-reliant in Asia" (Alex Kennedy, 'Singapore Sees Economy Growing 15 percent in 2010', Bloomberg Businessweek, July 14, 2010).

[15] Further evidence on the importance of economic openness and, in particular, the role of exports can be found in Briguglio, Cordina, Farrugia, and Vella (2009); Foxley (2009); World Bank (2010).

event study for the investigation of the impact of economic 'disasters'. During this period, the fall in output for many countries was the highest since the U.S. Great Depression, while many high interest rate currencies fell by 30% or more in the space of only a few months. The export dependence of each one of the 55 countries in the study is plotted on the horizontal axis of Figure 1a. Export dependence is measured as the average level of exports-to-GDP in the two years prior to the beginning of the financial crisis. The fall in real economic output (from pre-crisis peak to post-crisis trough) as measured by either industrial production or, when not available, real economic output, is plotted on the vertical axis. A statistically and economically significant relationship emerges: countries more reliant on exports exhibited larger falls in economic activity during the crisis.

In Figure 1b, I plot the fall in economic activity against the average 25-delta risk reversal during August 2008 (i.e. on the eve of the financial crisis) for 35 countries. No relationship is evident ($R^2 \approx 0$). Many of the world's highest interest rate currencies (denoted in blue), including Australia, India, Indonesia and South Africa experienced the smallest – not the largest falls in economic activity. In fact, Japan, the country offering currency market 'insurance' against a crash experienced one of the largest drops in economic productivity during the global financial crisis – a facet not captured by the risk-reversal immediately before the crisis.

In the top panel of Figure 2, the 55 countries in the study are sorted into four portfolios based on their export dependence and export concentration. The portfolios are plotted against the average fall in economic activity (within the portfolio) during the global financial crisis. Export dependence is measured, as before, as the average ratio of exports-to-GDP prior to the financial crisis. To capture export concentration, I first sort countries by export dependence and then split the sample into two – high and low export dependent countries – and sort these two groups based on their market and product concentration and then divide the reordered currencies into four portfolios.

To capture the concentration of exports, I calculate the Export Concentration Ratio (ECR, also known as the Herfindahl-Hirschmann index) across both export markets and products, given by

$$H_j = \frac{\sqrt{\sum_{i=1}^{n}\left(\frac{x_i}{X}\right)^2} - \sqrt{\frac{1}{n}}}{1 - \frac{1}{n}} \tag{13}$$

where $H_j$ is the country-level index, $x_i$ is the value of exports to country $i$ or of product $i$, $X = \sum_{i=1}^{n} x_i$ is the total value of exports across countries or products, while $n$ is the total number of trading partners or export products. The ECR ranges from zero to one, whereby zero reflects the least concentrated and one the most concentrated export nation.

Countries with higher Export-to-GDP ratios experienced larger falls in economic activity during the global financial crisis. Moreover, countries with *lower* market and product concentration experienced the largest falls in economic activity – consistent with the 'hump' based explanation of Cadot et al. (2011) – with a monotonic pattern being observed across the four portfolios when plotted against export dependence and concentration. In the bottom panel of Figure 2, the first bar chart reflects the fall in economic activity of countries when grouped by the value of the currency risk-reversal against the US dollar. No clear pattern emerges and yet, for the same group of countries, the export dependence and concentration ratios show a clear monotonic pattern.

**Capturing the exposure to risk.** To capture currency risk exposure, I sort currencies into portfolios on the basis of a country's export-to-GDP ratios (I consider export concentration, in terms of market and product, in extensions). The safest countries, those with the lowest export dependence, are included in the first portfolio. Risky countries, with the highest export dependence, are placed in the final portfolio. I form the risk factor in one of two ways: 1) taking the difference in returns on the highest and lowest portfolio returns, and 2) taking the average return on the first and second portfolios as well as the fourth and fifth portfolios, and then taking the difference between these returns. The second approach attempts to provide greater flexibility to the theory by allowing for a wider grouping of 'risky' and 'safe' countries, while reducing the measurement error of using a proxy for 'risk exposure'.

**Data.** I obtain monthly data on industrial production and quarterly data on exports and GDP from the IMF's *International Financial Statistics* database between 1983 and 2011. Data on export concentration is collected from the IMF's *Direction of Trade* database and includes monthly bilateral export data for 215 countries from 1983 to 2011. One-month risk reversals are over-the-counter quotes from JP Morgan.[16] Export concentration by product is calculated using data from the United Nations Conference on Trade and Development (UNCTAD). UNCTAD's database on merchandize exports by product is recorded yearly from 1995 onwards and includes data on the dollar value of exports for 255 different products.

[16]The sample comprises 35 countries: Argentina, Australia, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Euro area, Hong Kong, Hungary, Iceland, India, Indonesia, Israel, Japan, Malaysia, Mexico, New Zealand, Norway, Peru, Philippines, Poland, Russia, Singapore, Slovak Republic, South Africa, South Korea, Sweden, Switzerland, Taiwan, Thailand, Turkey, and UK.

## 3.4 Time-Varying Consumption-Surplus Ratio

**Summary of the model.** Verdelhan (2010) constructs a model based around external-habit preferences, building closely on the earlier closed-economy work of Campbell and Cochrane (1999). Countries with low interest rates are shown to be experiencing 'bad times', in that the representative investor's aggregate level of consumption is near the subsistence (habit) level. Investors in low interest rate economies are the most risk averse, and hence require the highest expected return from investing in foreign currency bonds. Due to the link with habit preferences, the underlying source of country heterogeneity is its current surplus-consumption ratio. Surplus consumption is defined as the percentage gap between consumption and the habit level ($S_t = [C_t - H_t]/C_t$), where $C$ is the level of consumption and $H$ is the habit level of consumption. In the model, the surplus-consumption ratio is given by the following autoregressive expression

$$s_{t+1} = (1-\phi)\bar{s} + \phi s_t + \lambda(s_t)(\Delta c_{t+1} - g) \tag{14}$$

where $g$ is the average consumption growth rate and $\lambda(s_t)$ describes how habits are formed from past aggregate consumption.

The interest rate differential between two countries is given by

$$r_t - r_t^* = -B(s_t - s_t^*). \tag{15}$$

where $s^*$ is the surplus-consumption ratio in the foreign country. $B$ has a negative coefficient and hence interest rates are low in bad times and high in good times. Furthermore, the interest rate differential will be positive when the surplus-consumption ratio is higher and economic conditions are better, in the domestic economy.

**How the prediction is empirically tested.** The author performs two exercises using real data. First, a calibration is performed using US and UK data, which delivers the negative coefficient from Fama regressions and matches the moments of consumption growth and real interest rates. The second exercise is more closely related to this study, in which the main preference parameters of the model are estimated for a US investor, using data on currency and equity portfolio returns. The estimated parameters are found to be closely related to previously documented parameter estimates from the habit-utility literature, while the pricing errors are not significantly different from zero in five of eight cross-sectional asset pricing tests. In this study, however, the focus is on the nature of the risk exposure and hence the importance is attached to the way currencies are sorted. Rather than make use of (potentially badly measured) aggregate consumption data across *all* countries, a proxy needs to be introduced to capture 'surplus consumption' across each country in the study.

**Capturing the exposure to risk.** Campbell, Pflueger, and Viceira (2014) model the surplus consumption ratio as a linear function of a country's output gap. The authors document empirical evidence that there is a particularly strong link in the U.S. between a stochastically detrended series of log real consumption and the log output gap (correlation of 90%). In fact, the output gap – the 'difference between the actual output of an economy and its potential output' (IMF, 2013) – is a widely used empirical measure of whether a country is currently experiencing an economic downturn, or 'bad time'. The measure could, therefore, be viewed as a proxy for the difference between the representative agent's level of consumption (actual output) and the 'habit' level (potential output).

In Figure 3, I document the link between the output-gap of a country and its forward-premia with respect to the US (calculated as the difference between the current forward premia and average forward-premia over the past two years) for four countries: Australia, Japan, Switzerland and UK. The series line-up closely. As suggested by the theory, the higher the surplus-consumption ratio, the higher the forward premia. Moreover, the output gap is a particularly good representation for the surplus-consumption ratio because of the relatively high level of volatility it generates – compared with aggregate consumption growth – while also exhibiting the property of being a highly persistent series, a feature of the surplus-consumption ratio regularly observed in calibrations of the habit-based model.[17]

**Risk factor.** To reflect the model, I sort currencies into portfolios on the basis of each country's output gap every period. To calculate the output gap, I first estimate the trend in real output using an Hodrick and Prescott (1997) filter, the output gap is then calculated as the difference between the actual and trend level of real output. Safe countries are those with the lowest (most negative) output gap and are included in the first portfolio. Risky countries are those currently operating above potential output, hence those countries with the highest output gap are included in the riskiest (fifth) portfolio. To form the risk factor, which captures cross-country differences

[17]In the habit model, the difference between actual consumption and habit consumption is never less than zero. But the same principal applies here. Over time the habit level changes (potential output changes) and utility of consumption is always measured relative to the habit level, i.e., actual output is measured relative to an economy's potential output.

in the surplus-consumption ratio, I form two alternative risk factors, in an analogous fashion to that described in the previous sub-section for the 'resilience to global shocks' factor.

**Data.** Quarterly data on nominal GDP and the GDP deflator are collected from the IMF's *International Financial Statistics* database.

### 3.5 Share of World Consumption

**Summary of the model.** Colacito and Croce (2013) construct a recursive preferences model of currency premia, considering situations with and without long-run risks. Within the model, a country's 'share of world consumption' ($SWC$) accounts for the asymmetry in countries' exposure to risk and is defined as

$$SWC_t = \frac{x_t + p_t y_t}{X_t + p_t Y_t} \tag{16}$$

where $x$ is the quantity of home consumption of the home good, $y$ is the home consumption of the foreign good, $X$ and $Y$ are the total output of the home and foreign good, while $p$ is the relative price of the two goods.

In a mean-variance-style trade-off, investors prefer higher levels of consumption but dislike volatility in their future consumption stream. Countries with the highest share of world consumption are most exposed to aggregate consumption shocks as a consequence of having fewer opportunities for international risk sharing. An investor in a smaller (lower consumption) open-economy, such as Switzerland, would therefore be expected to earn a premium by investing in larger (higher consumption) open economies, such as Australia or Brazil.[18]

**How the prediction is empirically tested.** Within the model, the determinant of excess currency returns is principally driven (under certain parameter conditions) by the volatility of continuation utility. The higher the volatility of continuation utility within an economy, the higher the expected return from investing in the economy. Using US and UK data, the authors show that, as predicted within the model, the volatility of continuation utility is an increasing function of $SWC$ and, hence, the riskiness of a country is a function of its share of world consumption.

[18] The model has similarities with the model's of Hassan (2013) and Martin (2013), who both find that a country's size is important for determining a country's exposure to risk in the world economy. The difference is, however, that the implications for currency betas are reversed. In the model of Hassan (2013), for example, a larger country is found to issue the 'insurance' bond and hence, offer a lower rate of interest on its bonds – not higher. The cross-sectional asset pricing results for these two cases are thus approximately equal to those for Colacito and Croce (2013), when the sign on the factor is multiplied by minus one.

The authors do not, however, consider more currencies. In part this reflects the two-country nature of the model and requirement for countries to be active trading partners – a caveat I take into consideration when capturing the model's prediction.

**Capturing the exposure to risk.** To reflect the model, I sort currencies into portfolios on the basis of a country's aggregate household consumption. The currencies of countries with low relative consumption are placed in Portfolio 1 (the safest). Countries with high consumption have their currencies placed into Portfolio 5 (the riskiest). The factor capturing the share of world consumption is then constructed as in the previous two cases. As previously noted, the model of Colacito and Croce (2013) is a two-country model with a focus on countries which are openly trading with one another. For the purposes of the empirical analysis, particular focus will therefore be placed on the smaller, developed country subsample, in which all the countries are open economies and make up a large proportion of total global trade.

**Data.** International data on 'household final consumption expenditure' (denominated in U.S. dollars), is collected from the World Bank's *World Development Indicators* (WDI) database. The sample runs from 1982 to 2011.

## 3.6 Alternative Characteristic Factors

Alternative characteristic factors are constructed using the Political Risk Services (PRS) Group's *International Country Risk Guide* (ICRG) database. The data is comprised of three composite indices as well as 22 sub-indices for each of the 55 countries in the sample, and spans macroeconomic, financial and political risks. The sub-indices are split across the three risk categories: 12 political risks including: (i) government stability, (ii) socioeconomic conditions, (iii) investment profile, (iv) internal conflict, (v) external conflict, (vi) corruption, (vii) military in politics, (viii) religious tensions, (ix) law and order, (x) ethnic tensions, (xi) democratic accountability and (xii) bureaucracy quality; five macroeconomic risks, including: (i) GDP per capita, (ii) real GDP growth rate, (iii) annual inflation rate, (iv) budget balance as a percentage of GDP and (v) current account as a percentage of GDP; and finally five financial risks, including: (i) foreign debt as a percentage of GDP, (ii) foreign debt service as a percentage of exports of goods and services, (iii) current account as a percentage of exports of goods and services, (iv) net international liquidity as months of import cover and (v) exchange rate stability.

To construct the alternative characteristic factors, I sort currencies into five portfolios, based on each underlying risk metric or 'characteristic'. The riskiest countries for each category are placed into the fifth portfolio, while the safest currencies are assigned to the first portfolio. To construct the factors to be used in cross-sectional pricing tests, I calculate the average return on the fourth and fifth portfolios each month, as well as on the first and second portfolios, and take the difference in returns on these two series. By doing so, I aim to reduce the measurement error associated with the ICRG data, which is constructed by assigning a relative, rather than absolute value to each of the predefined risks in the database.[19] The data are collected monthly between January 1984 and July 2011.[20]

### 3.7 Summary Statistics

In Table 1, I present summary statistics for *All Countries* and *Developed Countries* across the three theory-driven sorts, as well as for the five forward-premia-sorted portfolios. Currencies sorted by their forward premia generate a substantial cross-sectional spread of 8.32%, with the expected returns increasing monotonically from the first to the fifth portfolio. The same is true for the smaller *Developed Countries* sample, albeit with a slightly smaller spread (7.08%). As argued by Brunnermeier, Nagel, and Pedersen (2008), countries with the highest interest rate tend to have a larger skewness and hence, could be more exposed to 'crash' risk. There is no clear pattern, however, across the different portfolio volatilities and hence the high-interest portfolios are associated with larger Sharpe ratios in both samples.

The portfolios sorted on the basis of the resilience to world disasters do not, however, generate a large spread. The difference in returns on the extreme portfolios is less than 1% for *All Countries* and 1.5% for *Developed Countries*. This time, there is no obvious pattern in either the standard deviation, skewness or kurtosis across the portfolios, while the Sharpe Ratios are approximately equal across portfolios. The portfolios sorted on the basis of the time-varying consumption-surplus ratio generate a much larger spread in returns, of up to 4.64% for the *Developed Countries* sample. Furthermore, the skewness in portfolios for *All Countries* is similar to that across the five portfolios sorted by forward-premia – significantly lower for the riskiest (fifth portfolio) than for the first; however the pattern disappears for the *Developed Countries* sample, while the $HML$ portfolios exhibit zero or positive skewness. Nonetheless, due to the lack of variation in volatility across the

[19] For example, each country is assigned an overall score for each risk category, by which lower scores represent higher overall risk. In the composite indices, political risk is scored out of 100 (split, not necessarily equally between the 12 political risks), while economic and financial risk are both scored out of 50, due to being comprised of fewer sub-indices.

[20] Further information on how each risk category is constructed can be found at http://www.prsgroup.com

five portfolios, the Sharpe ratios do rise monotonically across the five portfolios in both samples. Indeed, for the *Developed Countries* sample, the Sharpe ratio is 0.56, almost equivalent to the 0.64 observed for the forward-premia-sorted portfolios, yet without the large negative skewness associated with the latter.

Finally, the portfolios sorted on the basis of the share of world consumption generate a *negative* spread in expected returns. Countries with a higher share of world consumption offer a *lower* expected return. This finding is consistent across both samples and, in fact, is more pronounced for the *Developed Countries* sample in which countries are more likely to be open and freely trading partners. The median return is even lower across the two samples (-1.55% and -5.00%), although the effect is apparently not driven by skewness – which is not clearly linked to the portfolio returns, nor volatility, which is approximately equal across portfolios.

# 4 Skeptical Asset Pricing and Simulations

The now increasingly standard set of test-asset portfolios, adopted in the empirical currency literature, are forward-premia-sorted portfolios proposed by Lustig and Verdelhan (2007) and extended upon by Lustig et al. (2011). Given the relatively low number of assets in the currency universe, particularly when compared with the equity market, the number of test asset portfolios is small in application. In the recent literature the number of test asset portfolios has included eight (Lustig and Verdelhan, 2007), six (Lustig et al., 2011), five (Della Corte, Riddiough, and Sarno, 2014; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012) and four (Mueller et al., 2013).

Two concerns arise from the approach. First, the number of test assets raises immediate concerns over the legitimacy of inference from cross-sectional tests with only a handful of data points. The second concern is subtler and was first addressed by Lewellen, Nagel, and Shanken (2010). Essentially, if test asset portfolios are characterized by a strong factor structure, which is true of the forward-premia sorted portfolios (Lustig et al., 2011), the power of cross-sectional tests to reject candidate risk factors is substantially reduced.

Attempting to distinguish between competing explanations for currency beta variation could, therefore, be contaminated by these fundamental statistical concerns. Before moving on to the formal empirical investigation of the model predictions, I begin by addressing these statistical concerns by examining the extent of the problem for currency market factors. In particular, I focus on whether 'useless' factors are priced in cross-sectional tests (Lewellen et al. (2010) focus instead on the OLS $R^2$ statistic when pricing equity portfolios), and investigate possible solutions to mitigate the problem.

**Macroeconomic and financial risks.** In Table 2, I examine the ability of the macroeconomic and financial risks from the ICRG database to explain the excess returns to the standard set of five forward-premia sorted test assets. In Panel A, I report results for financial risks. Fama-MacBeth estimates for the price of risk are shown for both *DOL* and the *HML* factor (constructed as described in the previous section) with associated standard errors. Every factor is found to be priced, with the t-statistic over 3.0 for the composite financial risk. The cross-sectional $R^2$ statistics are also impressive, ranging from 62% to over 91%. The *RMSPE* varies across models, with the lowest (0.66%), being generated by the FX Stability factor (based on the previous year's volatility of the exchange rate vs the US dollar). Likewise, the lowest $\chi^2$ statistic is also generated by the FX Stability risk, while three of the factors produce pricing errors not statistically different from zero. The correlation with the second principle component of the test asset returns ($\rho$) is also relatively high for many of the factors. For aggregate financial risk the correlation is over 50%, while for the Current Account (CA) factor (CA as a percentage of exports of goods and services), the correlation is over 40%.

In Panel B, I report results for macroeconomic factors. The results are now even stronger. The t-statistics for each of the factors are over 2.0 and, in four cases, are over 3.0. The goodness-of-fit statistics are also strong. The $R^2$ statistics range from 72% for the composite economic risk to 92% for GDP per capita. The correlation with the second principle component is also high and over 40% for current account risk (CA as a percentage of GDP), inflation risk (annual inflation rate) and GDP per capita. As found in previous studies, the *DOL* factor is never priced, but instead works as a constant within the model. The impressive performance of the financial and macroeconomic factors is explored further in Figure 4. Here, I document the returns to the financial and macroeconomic risks, conditional on the returns to the carry trade. I therefore split returns to the carry trade into quintiles (from low to high) and calculate the average return to the HML-style factors. The majority of factors display a monotonic type pattern, suggesting a common risk is at work, which all the factors are correlated with. It does not, however, reveal causality or provide information regarding which factor is the most important for understanding currency risk exposure.

To pursue the point further, in Table 2, I also report the average return for each of the *HML* factors. Strictly, the mean and price of risk should be the same – the factor *must* have a $\beta$ equal to one when pricing itself. Lewellen et al. (2010) show that for a single risk factor, it will only exhibit a price of risk equal to its mean *if* the correlation with the 'true' risk factor (here, the second principle component of the test asset returns) is equal to one. Imposing this restriction and examining pricing errors may be too strict and would lead to the rejection of factors which may contain, at least some, economic content on the source of risk exposure. Nonetheless, the difference between mean returns and estimated factor prices of risk are large and, in a number of instances fall outside the range of two times the estimated standard error.

**Simulated 'useless' factors.** In Table 3, I extend the analysis by investigating the pricing ability of artificially generated factors. I construct two sets of artificial currency factors. The first, which I denote 'useless factors', are formed by randomly allocating currencies to one of five portfolios every month. I then form a *HML* factor by taking the difference in returns on the extreme portfolios. I construct 20,000 factors in this fashion. The second method randomly generates portfolio weights for each of the five test asset portfolios and forms a dollar-neutral portfolio each month (I rescale the weights such that each month the portfolio is long and short one dollar). I again run the exercise 20,000 times and denote the factors 'random weights'.

In Panel A, I examine the pricing power of these artificially constructed factors with the five forward-premia-sorted test assets. Due to the artificial nature of these factors, their correlation with the second principle component is low. Virtually no factor has a correlation over 30%, offering evidence from the previous exercise that macroeconomic and financial risks could help explain the source of currency risk exposure. Yet despite the low correlation, the factors generate overwhelmingly high t-statistics. No matter whether the factor prices of risk are estimated using a Fama-MacBeth (*FMB*) or Generalized Method of Moments (*GMM2*) estimation, the proportion of t-statistics falling above the asymptotic level is high. Around 40% of the factors are found to be 'priced' when adopting the *FMB* approach, with the level falling to around 20-25% with *GMM2*. Likewise, the goodness-of-fit statistics are also high. The $R^2$ is over 70% for around a quarter of 'random-weight' portfolios, although the adjusted GMM2 $R^2$ is much lower, with only a quarter of models generating an $R^2$ over 30%. Furthermore, only 21% of the 'random weight' models generate a *p-value* less than 5% (28% for the 'useless factors'), implying around three-quarters of the factors are capable of 'explaining' the cross-sectional spread in portfolio returns.

**Mitigating the problem.** To address the problem, Lewellen et al. (2010) suggest three main solutions:

1. Examine the Generalized Least Squares (GLS) $R^2$ statistic.

2. Include more test-assets to break the strong factor structure.

3. Include the return-based risk factors as test asset portfolios.

In Panel A of Table 3, I report adjusted $R^2$ statistics from the *GMM2* procedure. This statistic reflects the GLS $R^2$ statistic and, as seen, significantly reduces the models' goodness-of-fit. In Panel B, I adopt the second and third proposed measures. When testing the 20,000 'useless factors', I add both the $DOL$ and $HML$ risk factors as well as the five randomly constructed portfolios as test assets, such that 12 currency portfolios are tested in total. For the 'random weight' factors, I add just the $DOL$ and $HML$ risk factors to the test asset group, to assess if adding more test assets is particularly important, or whether the simply including the return-based risk factors is sufficient to restore the power of the statistical tests. The addition of the return-based risk factors forces the estimated $\beta$ of the risk factor to be equal to one in the first stage of the *FMB* procedure. It thus works in a similar fashion to imposing that the price of the risk equals the average return of the factor.

The *FMB* t-statistics are now more closely aligned with their asymptotic equivalent, with only 4.3% of 'useless' factors and 6.1% of 'random weight' factors generating a t-statistic over 1.96. The *GMM2* t-statistics tend, however, to over-reject the factors. Less than 1% of the random factors are found to be 'priced' in the new exercise, while less than 2% are priced at the 10% critical threshold (compared to 9% and 12% when adopting the *FMB* procedure). A similar pattern emerges for the model fit statistics. With *GMM2*, less than 1% of factors generates an adjusted $R^2$ statistic over 5%, while every factor would be rejected using the $\chi^2$ statistic. The *FMB* procedure is less strict but still penalizes most factors. Less than 1% of 'useless' factors generate a *p-value* on the $\chi^2$ test less than 0.05 (less than 9% for the 'random weight' factors), while only 10% of useless factors (2.3% of 'random weight' factors) generate a model $R^2$ over 30%.

To see the impact on the t-statistics more clearly, in Figure 5, I present the histograms of t-statistics for both the 'useless' and 'random weight' factors when pricing the five forward-premia-sorted portfolios as well as the additional test asset portfolios. Before the addition of more test-assets, the t-statistics form a bi-modal distribution, with a large share of factors exhibiting a t-statistic in excess of 2.0 (in absolute terms). When more test asset portfolios are included, the distribution of t-statistics changes considerably, and is virtually indistinguishable from a Gaussian distribution – even with only the inclusion of the two pricing factors as test asset portfolios.

From the results it appears sensible to employ more test assets, with the inclusion of the return-based risk factors being particularly important, while the inclusion of the five additional portfolios helps to shift the results (particularly the t-statistics) towards the conservative side. Yet, an overly insistent position on efficiency could be *too* harsh. A factor generating a *GMM2* t-statistic less than 2.0 may still contain economic content and should be considered holistically with other factors such as the *FMB* $R^2$ and t-statistics, rather than being immediately rejected. In fact, once the additional test portfolios are included, an FMB t-statistic exceeding 2.0 *is* suggestive of economic content in explaining currency portfolio returns.

# 5 Asset Pricing Results

In this section, I present the results from cross-section and time series asset pricing tests for the theory-driven risk factors, as described in Sections 2 and 3. Building on the results of Section 4, I assess the asset pricing performance using both 12 and 22 test asset portfolios, always including the risk factors as test assets.

## 5.1 Cross-section results

In Table 4, I present the cross-sectional asset pricing results for *All Countries*. Results are presented for 12 test asset portfolios in Panel A and for 22 test asset portfolios in Panel B. I include results from the first and second stage Generalized Method of Moments estimation (*GMM1* and *GMM2*) as well as for the Fama-MacBeth procedure (*FMB*). For *GMM1* and *GMM2* I initially estimate the $b$'s from the reduced-form Stochastic Discount Factor (SDF), which are then translated into standard factor prices of risk $\lambda$ following the technique described by Cochrane (2005). With the *FMB* procedure I move directly to calculate the factor prices of risk. I report standard errors in parentheses. In the case of 12 test asset portfolios, I include the five commonly adopted forward-premia sorted portfolios, the two risk factors (*DOL* and *HML*) as well as the five portfolios sorted by the predicted source of risk (i.e. for the time-varying surplus consumption factor, I also include the five portfolios sorted on the basis of countries' output gap). In the case of 22 test asset portfolios, I add to the 12 portfolios the five portfolios sorted by the predicted source of risk from the alternative two theories investigated in the study.

**Resilience to world disasters.** The performance of the factor constructed to reflect countries' resilience to world disasters, is reported in the left-hand columns. The factor price of risk is found to be negative and insignificant in all three tests and across both 12 and 22 test asset portfolios. As documented previously, the *DOL* risk factor is not statistically significant in any test. The goodness-of-fit statistics are also disappointing. The OLS $R^2$ from the *FMB* procedure is 21.2% (13.9%) but falls to 3.7% (1.9%) for the OLS adj-$R^2$, and -4.3% (1.9%) for the GLS adj-$R^2$ when investigating 12 (22) portfolios. Moreover, the correlation of the factor with the second principal component of forward-premia-sorted portfolio returns is negative (-21%). In the remaining tests of model fit, the pricing errors are found to be statistically different from zero (a high $\chi^2$ test statistic and hence low p-value is observed across tests), while the RMSPE is almost 1.5% when using 12 test asset portfolios and 1.3% for 22 test asset portfolios.

**Share of world consumption.** In the right-hand columns, I report the results for the factor reflecting a countries share of world consumption. The factor is, once again, not significant in any of the tests. In fact, the factor prices of risk estimated in *GMM1* and *FMB* are negative, for both sets of test asset portfolios, while the $b$'s from the SDF are also found to be negative and insignificant. The goodness-of-fit statistics also demonstrate the model's lack of pricing power. The OLS and GLS adj-$R^2$ are always negative (reaching a low of -24.7%), while the $\chi^2$ test statistics and RMSPE's are similar to those estimated previously for the resilience to world disasters factor, with a RMSPE of around 1.5% (1.3%) for 12 (22) test asset portfolios.

**Time-varying surplus consumption.** The cross-section results for the final theory-based factor, constructed to reflect countries time-varying surplus-consumption ratio, is reported in the middle set of columns. The factor price of risk is now significant at standard confidence levels for both GMM1 and GMM2 and is found to have a t-statistic around 3.0 when estimated using the *FMB* procedure. The factor should also exhibit a $\beta$ of one when pricing itself and indeed, I find that the estimated factor price of risk (3.18% and 3.13%) is not more than 50 basis points from the factor's mean return in either the *GMM1* or *FMB* procedures, and is exactly equal to the factor's average return in the more efficient *GMM2* estimation.

The goodness-of-fit statistics for the surplus-consumption factor are also strong. The $R^2$ statistic is almost 50% when pricing 12 test asset portfolios (recall that only 0.5% of artificially generated factors yielded an $R^2$ over 50% in the simulation exercise), while the GLS adj-$R^2$ is 28.5% and 32.3% for the two sets of test assets (in simulations only 1.2% of randomly constructed factors generated a GLS adj-$R^2$ over 30%). The RMPSE's are also between 10% and 30% lower than for the previously examined models. It is also notable, that only the surplus-consumption factor generates a positive correlation with the second principal component of forward-premia-sorted portfolio returns – a characteristic common to all the financial- and macroeconomic-based factors examined in Table 2.

**Developed countries.** Two possible concerns may arise in the readers mind. First, the *All Countries* sample includes a number of emerging market countries, which may be either pegged or semi-pegged to another currency. Second, the focus of a theoretical model may be on developed rather than emerging economies. Indeed, as noted earlier, the model of Colacito and Croce (2013) requires countries to be trading partners and hence, for an $N$-country investigation, the countries examined should be firmly integrated into the world economy. To mitigate these concerns, I investigate a set of asset pricing tests using a smaller sample of *Developed Countries*. Full details of the countries included in the sample can be found in Section 3.

**Resilience to world disasters.** In Table 5, I again consider 12 and 22 test asset portfolios and in every other respect, the investigation proceeds as before for the *All Countries* sample. In the case of the factor reflecting the resilience to world disasters, the results remain broadly unchanged. The factor prices of risk are no different from zero. Furthermore, the factor is negatively correlated with the second principal component of forward-premia-sorted currency returns and is unable to explain any of the cross-section of expected returns (GLS adj-$R^2 \approx 0$). The RMPSE's are also significantly higher (around 20 to 30 basis points) compared to the other two theory-driven models.

**Share of world consumption.** A larger difference in results arises for the share of world consumption factor (Colacito and Croce, 2013). The factor price of risk is found to be insignificant when estimated using *GMM1* and *GMM2* but, as documented in Section 4, this benchmark may be overly restrictive. In the case of the *FMB* procedure the factor is on the borderline of significance (between the $5^{th}$ and $10^{th}$ percent confidence levels), however, the factor generates a *negative* risk premia. This finding indicates that countries with the *lowest* share of world consumption – even among the most developed G10 set of countries – offer the highest currency premia, not the lowest. The finding suggests the models of Hassan (2013) and Martin (2013), which both predict that smaller countries (by national output) will offer the highest currency premia are partially supported by the data (albeit on the borderline of statistical significance) for developed countries, but *not* for a larger sample of emerging economies. In fact, the cross-sectional goodness-of-fit is particularly strong in this case, with the OLS $R^2$ reaching as high as 59%, while even the GLS adj-$R^2$ is over 30%.

**Time-varying surplus consumption.** The best performance is, however, once again from the surplus-consumption factor of Verdelhan (2010). The factor price of risk is significant in all cases and, in fact, remains relatively unchanged from the previous estimation when employing the larger sample of currencies. The t-statistic is over 3.0 when estimated using the *FMB* procedure, while the GLS adj-$R^2$ is close to 50% – implying especially strong pricing power, particularly in light of the earlier simulation exercises. The RMSPE's are also the lowest across the three models, fluctuating between 90 and 100 basis points across the two sets of test asset portfolios.

**Pricing errors.** In Figure 6, I display the pricing errors generated by the three factors for both the 12 and 22 portfolio sets of test assets, across the *All Countries* and *Developed Countries* samples. As expected from the cross-sectional results, the pricing errors from the surplus-consumption factor lie closest to the $45^o$ pricing line (deviations from the pricing line indicate model mispricing). The predicted returns, generated by the factors reflecting countries' resilience to world disasters and the share of world consumption, display little-to-no relationship with the expected portfolio returns. Nonetheless, despite the better performance of the surplus-consumption factor, scope remains for other factors to provide incremental information in explaining expected currency returns, and hence for developing our understanding of currency risk exposure. I explore this possibility further in Section 6.

## 5.2 Time-series results

**All countries.** In Table 6, I report the results from the first-stage Fama-MacBeth time-series regressions for *All Countries*, when pricing 12 portfolios. The first five portfolios represent the commonly tested forward-premia-sorted test assets, in which the first (fifth) portfolio contains the lowest (highest) interest rate currencies. Across all three models, the $\beta_{DOL}$ estimate is significant and close to one, indicating currencies tend to appreciate and depreciate in synch against the US dollar. The estimated coefficient on the theory-specific risk factor $\beta_{HML}$, does however, fluctuate across portfolios and across models. High interest rate currencies have been shown to have the largest loading on global risk (Lustig et al., 2011), and therefore it follows that for the theory-driven factors to accurately capture currency risk exposure, low interest rate currencies should load negatively on the factor (lowest currency beta), while high interest rate currencies should load positively (highest currency beta). Moreover, the same monotonic pattern of beta loadings, should also be observed on the five currency portfolios sorted by the predicted source of risk exposure.

The coefficients on the resilience to world disasters factor, are found to be insignificant across four of the five forward-premia sorted portfolios. In fact, the point estimate is positive in each case except for portfolio five (the riskiest portfolio), for which a statistically significant but *negative* coefficient is observed. The $R^2$ statistic is found to be high across all the regression specifications tested. This result reflects the important contribution of the *DOL* factor from a time-series perspective – a large share of the time-series variation in returns can be accounted for by the numéraire effect, coming from fluctuations in the US dollar.[21] The loadings on portfolios sorted by the export-to-GDP ratio are, however, found to generate a monotonic spread, a characteristic common to each of the three theory-driven factors and portfolios.

The factor reflecting the share of world consumption is also found to be largely unrelated to the forward-premia-sorted test assets. Again, four of the five coefficients are not statistically different from zero. The coefficient is only significant on the first portfolio (the safest portfolio) but the loading is positive, indicating that low-interest-rate currencies have a *higher* exposure to risk. Only the time-varying surplus-consumption factor generates time-series coefficients consistent with the theory, thus providing a candidate explanation for why some currencies are more exposed to global risk than others. The spread is not perfectly monotonic but nonetheless, low yielding currencies do have the most negative currency betas, while the fifth portfolio has the highest currency beta. Furthermore, four of the five coefficients are found to be significant at the ten percent confidence level.

**Developed countries.** In Table 7, I present the analogous Fama-MacBeth time-series regression results for the smaller sample of *Developed Countries*. The $\beta_{HML}$ loadings for the resilience to world disaster risk factor are now significant in three cases, however no consistent pattern is observed in the factor loadings. The second portfolio, for example, is more exposed to risk than the first portfolio, while the fifth portfolio again has the most *negative* exposure. The share of world consumption factor *does* generate a monotonic spread in risk exposure, but from the highest-to-lowest interest rate currencies, in the opposite direction to the prediction of the theory.

Once again, the best performance comes from the surplus-consumption factor. None of the estimated constants $\alpha$, which represent model mispricing, are found to be statistically different

[21] Note, a similar effect would be observed were the numéraire to be changed to a different currency or good

from zero – indicating impressive model fit across test asset portfolios. Nonetheless, the absolute risk on the second and fourth portfolios is larger than on the extreme portfolios. Moreover, the $\beta_{HML}$ coefficients on the extreme portfolios are not statistically different from zero at the 10 percent confidence level.

**Are more factors required?** In the summary statistics, the global risk factor is seen to generate a larger unconditional return than any of the theory driven factors. In the *All Countries* sample the return on global risk is 8.32%, compared to 3.44% for the surplus-consumption factor (i.e., only accounting for 40% of the total carry trade return). In the *Developed Countries* sample the deviation is smaller but still economically significant (7.08% vs 4.64%). It thus follows that the surplus-consumption ratio contributes in part to the overall explanation, but allows space for other factors to provide incremental information on the determinants of currency betas.

In the next section, I explore this possibility further, by returning to the *PRS* Group data, previously examined in Section 4. Employing the stricter benchmark of pricing more portfolios and with stronger asset pricing tests, I seek to understand if any of the risks continue to be priced and, moreover, can provide additional information over-and-above the surplus-consumption ratio.

# 6 Financial, Economic and Political Characteristics

In Tables 8, 9 and 10, I examine the pricing performance of financial, economic and political risk factors constructed as described in Section 3. In Section 4, the strong pricing performance of both financial and macroeconomic-based risk factors was documented. This time, I raise the bar by examining the factor's pricing performance when explaining 12 currency portfolio returns (five forward premia sorted portfolios, five portfolios sorted by the same characteristic, and the two risk factors, *DOL* and *HML*). In particular, I focus on whether the factor is priced (a statistically significant $\lambda_{HML}$, in *FMB* regressions), adds incrementally to the *DOL* factor (a statistically significant $b_{HML}$ estimated in the more efficient *GMM2* procedure), generates relatively strong goodness-of-fit statistics compared to arbitrarily constructed factors (an OLS $R^2$ over 30% and GLS adj-$R^2$ over 10%), while also yielding a monotonic spread in beta loadings $\beta_{HML}$, when pricing the forward-premia sorted portfolios in the first-stage Fama-MacBeth regressions. The exercise is to ascertain which, if any, risks are incremental to our understanding of currency risk exposure, rather than to provide a *complete* description of currency risk and return.

Of the six financial risk factors, only the FX Stability factor (defined as the percentage appreciation or depreciation against the US dollar over the last 12 months), continues to be priced in the more rigorous empirical tests. In fact, the factor passes all the benchmarks raised above except for the monotonicity of the estimated $\beta_{HML}$ coefficients. The $\beta_{HML}$ coefficient on the first portfolio is also not statistically different from zero, although the general pattern of low-to-high coefficients *is* observed. The economic risks, presented in Table 9, continue to perform particularly well, suggesting there is a strong macroeconomic rationale for the variation in currency betas. Apart from the GDP growth rate, all the factors are statistically priced using the *FMB* procedure. The Aggregate Economic Risk, performs particularly well with the highest $R^2$ statistic and lowest RMSPE across all the economic factors. Nonetheless, the estimated $b_{HML}$, from the second-step *GMM2* estimation is not statically significant. This finding implies that while the factor may be correlated with the 'true' efficient frontier portfolio, it does not provide incremental information over the *DOL* factor in explaining the currency market SDF.

Of the remaining economic risks, GDP Per Capita (GDP per head as a % of average GDP across countries), the Budget Balance (central government budget balance as % of GDP), and the Current Account (as a % of GDP), are all priced factors *and* provide incremental information over-and-above the *DOL* risk factor. Moreover, the factors pass the goodness-of-fit benchmarks highlighted previously. The GDP Per Capita and Current Account factors also generate the monotonic spread in $\beta_{HML}$ loadings on the forward-premia-sorted test portfolios, while the Budget Balance factor generates an approximately monotonic spread in loadings, with low-interest-rate currencies negatively exposed to risk, and vice-versa for high-interest-rate currencies.

The weakest set of asset pricing results are generated by the political risk factors. In total 12 political risks are analyzed. I report the six main risks (as measured by their weighting within the Composite Political Risk Index) in Table 10, and the remaining six risks in the Internet Appendix. Only two of the political risks generate priced risk factors, the first is Socioeconomic Conditions, which is made up of three subcomponents: unemployment, consumer confidence and poverty. In essence, it captures the socioeconomic pressures within a society that could constrain government action or give rise to social unrest. Notably, the factor is one of only two political risks with large macroeconomic components, supporting the earlier view that macroeconomic risks form the primary driver of risk exposure.

The Investment Profile is the other political risk with a large macroeconomic component. It is also the only other political risk that is priced. The Investment Profile is a broad measure of the risk to an investment in the country. Like Socioeconomic Conditions, the risk is comprised of several subcomponents: contract viability/expropriation, profits repatriation and payment delays. Both of the macroeconomic dominated political risks pass the empirical asset pricing benchmarks. In particular, the factors generate strong goodness-of-fit statistics (OLS $R^2$ statistics of 42.1% and 44.1%) and the lowest RMSPE among all political risks. The time-series beta loadings have a monotonic pattern, while the extreme $\beta_{HML}$ coefficients are highly significant for both factors.

**Incremental pricing performance.** I examine the incremental pricing performance of the strongest performing financial, macroeconomic and political risks identified from the previous tests when combined with the factor reflecting countries' output gaps. Specifically, I investigate: FX Stability (financial), GDP Per Capita (Economic), the Budget Balance (Economic), the Current Account (Economic), Socioeconomic Conditions (Political) and the Investment Profile (Political). In Table 11, I explore the correlation structure of the risks, both relative to one another as well as to the Surplus-Consumption and *Dollar Risk* factors. In general the additional factors have low correlations with the Surplus-Consumption factor (the highest being the Current Account at 22% and Investment Profile at 15%) and negative correlations with the Dollar Risk factor (with the exception of currency volatility).

Among the factors themselves, the correlations are significantly higher. The Budget Balance, Current Account, Investment Profile, GDP Per Capita and Socioeconomic Conditions are all highly correlated with one another (correlations ranging between 20% and 50%); countries which are the riskiest on one macroeconomic dimension tend to be the riskiest on other macroeconomic dimensions as well. This finding also relates to recent evidence that the *unconditional* or 'static' component of the carry trade constitutes for a substantial portion of the overall return (Lustig et al., 2011; Hassan and Mano, 2014). Across all the highly correlated factors, the ranking of currencies by risk remains relatively stable across time, while it does not for the surplus-consumption ratio. It therefore appears as though the surplus-consumption ratio provides information regarding a countries *conditional* risk exposure, while other characteristics provide information on the *unconditional* exposure to global risk.

**Cross-sectional tests.** In Table 12, I present a series of asset pricing results for the seven risk characteristics, the surplus-consumption factor and *Slope* risk factor of Lustig et al. (2011). In Panel A, I run a large cross-sectional regression with all characteristic factors included. Fifty-eight test asset portfolios are included in the analysis (seven sets of five portfolios sorted by the characteristics under investigation, the additional 10 portfolios sorted on the basis of the theory-driven factors, five forward-premia sorted portfolios, the *DOL* factor as well as the seven *HML* style pricing factors). Once again, I test the significance of the factors in terms of being 'priced', as well as providing incremental information beyond the other factors by examining the $b$'s from *GMM2*. I also report *FMB* cross-sectional regression statistics.

In Panel A, only the Surplus-Consumption based risk factor and *Slope* factor are found to be priced at the 5% confidence level. Yet, the high correlation among the factors is likely to be masking the true causal factors due to multicollinearity reducing significance of some factors. Cochrane (2005), argues that the emphasis when evaluating competing risk factors should be the $b$'s from the SDF estimation rather than the cross-sectional $\lambda$ coefficient. In this case, even the Slope risk factor is found to be *insignificant*, likely due to the other risk factors capturing similar macroeconomic-based information. Nonetheless, the surplus-consumption-based factor does continue to remain significant ($b = 1.02$ and $SE = 0.33$) in the GMM2 test, indicating that the factor provides information incremental even to the *Slope* factor of Lustig et al. (2011).

To examine which of the characteristic factors provides the most incremental information, I drop the characteristic factor with the lowest t-statistic, and re-estimate the large cross-sectional regression (I do not include the Slope factor). I continue the process, iterating by dropping the factor with the smallest t-statistic, until only highly significant factors are left. Once complete, only the Surplus-Consumption, Investment Profile and Current Account factors remain. In Panel B, I examine the individual pricing performance of each of these factors, and compare them with the *Slope* factor, when pricing the 58 test asset portfolios. In each case the factors are priced, add incrementally to the *DOL* factor, and have strong goodness-of-fit statistics (cross-sectional mispricing not statistically different from zero). Nonetheless, the stricter GLS $R^2$ statistic is less flattering, particularly for the Investment Profile and Current Account factors (1.1% and -1.7% respectively), particularly when compared with the *Slope* factor (OLS $R^2 = 50.5\%$, GLS adj-$R^2 = 40.3\%$). This result may, however, simply reflect that none of the factors on their own can explain the variation in currency betas but, together, could provide considerable information on the nature of currency risk exposure.

**Incremental pricing factors.** I explore this possibility in Panel C. Again, I run cross-sectional regressions including the Surplus-Consumption ratio and either the Investment Profile or Current Account and then finally, add both additional factors. In the final specifications with all three additional factors included, I find each factor provides incremental information ($b$'s all statically significant – including the *DOL* factor), while the *FMB* estimated factor prices of risk are all significant. Moreover, the OLS and GLS $R^2$ statistics rise as each additional factor is included in the regression, reaching a high of 58.1%, with the RMSPE falling to a low of 0.83% – slightly lower even than for the *Slope* risk factor.

In Figure 7, I display the incremental pricing performance from adding the additional explanatory factors. In the top-left chart I display the pricing errors from including only the *DOL* factor. I add the Surplus-Consumption based factor in the top-right figure, which closely resembles the pricing errors observed in the middle charts of Figure 6. The addition of the Investment Profile and then Current Account factors, significantly improves the pricing performance, such that the final chart in the lower right-hand corner has the majority of points lying either close to, or on, the $45^o$ pricing line.

**Links with the literature.** The results are consistent with recent literature on the determinants of currency risk exposure. Della Corte et al. (2014) also sort currencies based on a source of risk conjectured by Gabaix and Maggiori (2014). According to the theory, holding currencies issued by countries with large external deficit positions, should generate higher expected returns. The finding is supported by Della Corte et al. (2014), and is consistent with the finding here, that the Current Account macroeconomic factor is priced. Nonetheless, this is not the entire story and, in fact, Gabaix and Maggiori (2014) make clear that this component should account for only part of the total carry trade return. Factors which could contribute to the remainder of the return include the transient surplus-consumption ratio, as proxied by countries' output gap, as well as the more permanent set of investment risks faced within the country. Indeed, Howe and Pigott (1992) and Orr et al. (1995) both examine the determinants of real interest rates and find that higher investment returns and 'investment risks' (with high external borrowing being particularly important), are the main drivers of real interest rates. As determined in Section 2, real interest rate differentials should be the main component of carry trade returns and, thus, the finding that a higher output gap (higher current return), high external borrowing and heightened investment risks are all priced factors, is consistent with these earlier findings.

# 7 Conclusions

This paper has examined the macroeconomics of risk exposure in models of currency risk premia. Assuming that excess returns are compensation for global risk, I have sought to understand *why* a currency is more (or less) exposed to that risk, rather than focus on the question of *what* the risk may be. In essence, unlike many empirical studies of asset prices, I consider the *quantity* of risk rather than treat it as a free-parameter. I begin by extracting the predictions of leading theoretical models of currency premia on the determinants of currency risk exposure. I argue that the models can be tested by sorting currencies into portfolios based on their predicted exposure to risk – allowing for a set of well-defined asset pricing tools and techniques to be employed.

If the portfolios generate a monotonic spread in returns and, if an $HML$-style factor constructed from those portfolios is 'priced', it provides evidence in support of the model's predictions. Specifically, I test three leading candidate models of currency premia, which cover the main variations of the consumption-based model: external-habits, long-run risks and variable rare disasters. I proxy for the underlying source of risk exposure and find the surplus-consumption ratio (proxied by a country's output gap) to be a strong predictor of currency excess returns. Countries with higher output gaps offer the highest currency premia, consistent with the model of Verdelhan (2010). Due to the high variability of country's output gaps, the finding offers guidance on the determination of the conditional currency carry trade return. The result is robust to the size of the sample, the number of test assets and to imposing the theoretical restrictions suggested by Lewellen et al. (2010).

In fact, the restrictions of Lewellen et al. (2010) are found to be particularly important. Using simulations and alternative characteristic factors, I find evidence that a large proportion of randomly generated factors, as well as broad macroeconomic and financial risks, are priced in cross-sectional tests. Nonetheless, when I impose a stricter empirical benchmark, I find some macroeconomic-based factors *can* provide incremental information on the nature of currency risk exposure. In particular, countries with the largest current account deficit as well as those with the weakest investment profile, are found to offer larger currency excess returns. The result provides guidance on the unconditional determinants of the carry trade return and supports recent work on the determination of currency premia, which focuses on countries' external deficit position.

Overall, the findings offer an alternative way for empiricists to test theoretical asset pricing models, by investigating the rationale for *exposure* to risk, rather than focusing entirely on the *definition* of risk. Moreover, the results provide guidance for future theoretical work seeking to provide a more complete description of both the price and quantity of currency risk by helping to identify the drivers of conditional and unconditional excess currency returns.

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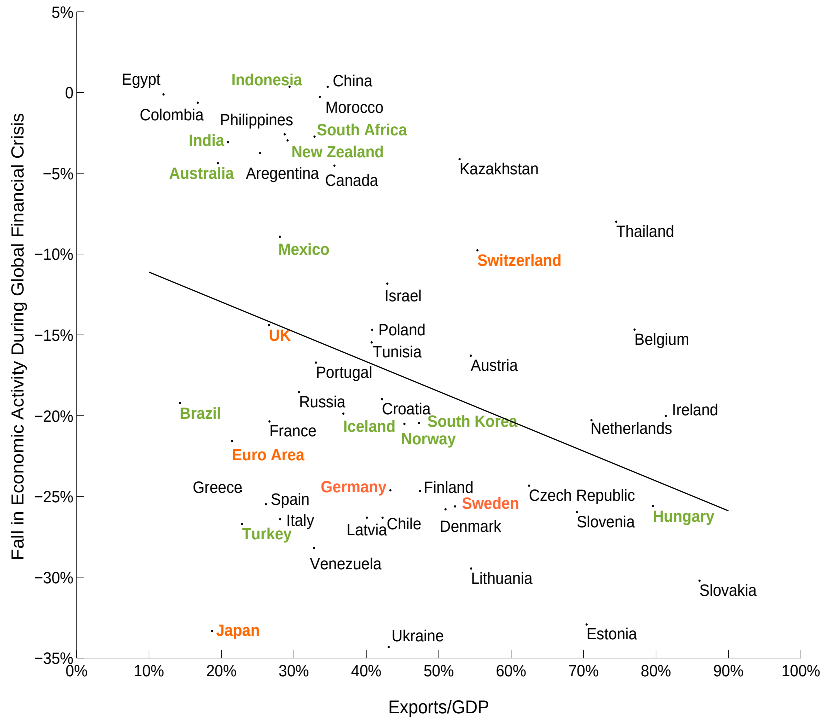
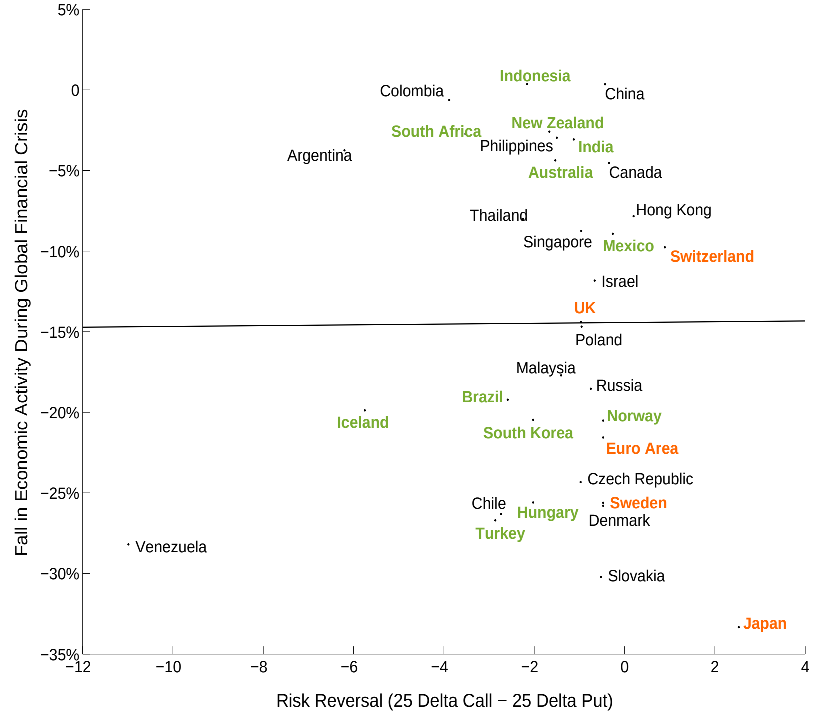



(a) Export Dependence and the Global Financial Crisis




(b) Risk-Reversals and the Global Financial Crisis

**Figure 1:** ***The Resilience of Countries to Global Shocks.*** *The figure presents the relationship between proxies, for countries' resilience to world economic disasters, and the fall in economic output during the global financial crisis. In Figure (a), the proxy is given by a country's dependence on exports as measured by the Exports-to-GDP ratio. The value is calculated by averaging the Exports-to-GDP ratio for each country between 2006 Q2 and 2008 Q2. In Figure (b) the proxy is the risk reversal for each currency relative to the US dollar. The risk reversal is calculated as the difference between a 25 delta call and 25 delta put. Currencies with the most negative risk reversal are the ones with the highest probability of experiencing a large depreciation in the future. The value is calculated as the average value of the risk reversal in August 2008. The fall in economic activity is measured as the percentage decline in economic output from the peak (pre-crisis) value of either real GDP or real industrial production to the trough (crisis) level of economic activity. Data on real GDP, nominal GDP, industrial production and exports are collected from the IMF's International Financial Statistics database except for Venezuela and Kazakhstan, for which industrial production data was collected from National Statistical agencies. Data on risk reversals are over-the-counter quotes from JP Morgan, kindly provided by Pasquale Della Corte.* *[Go to page 13].*

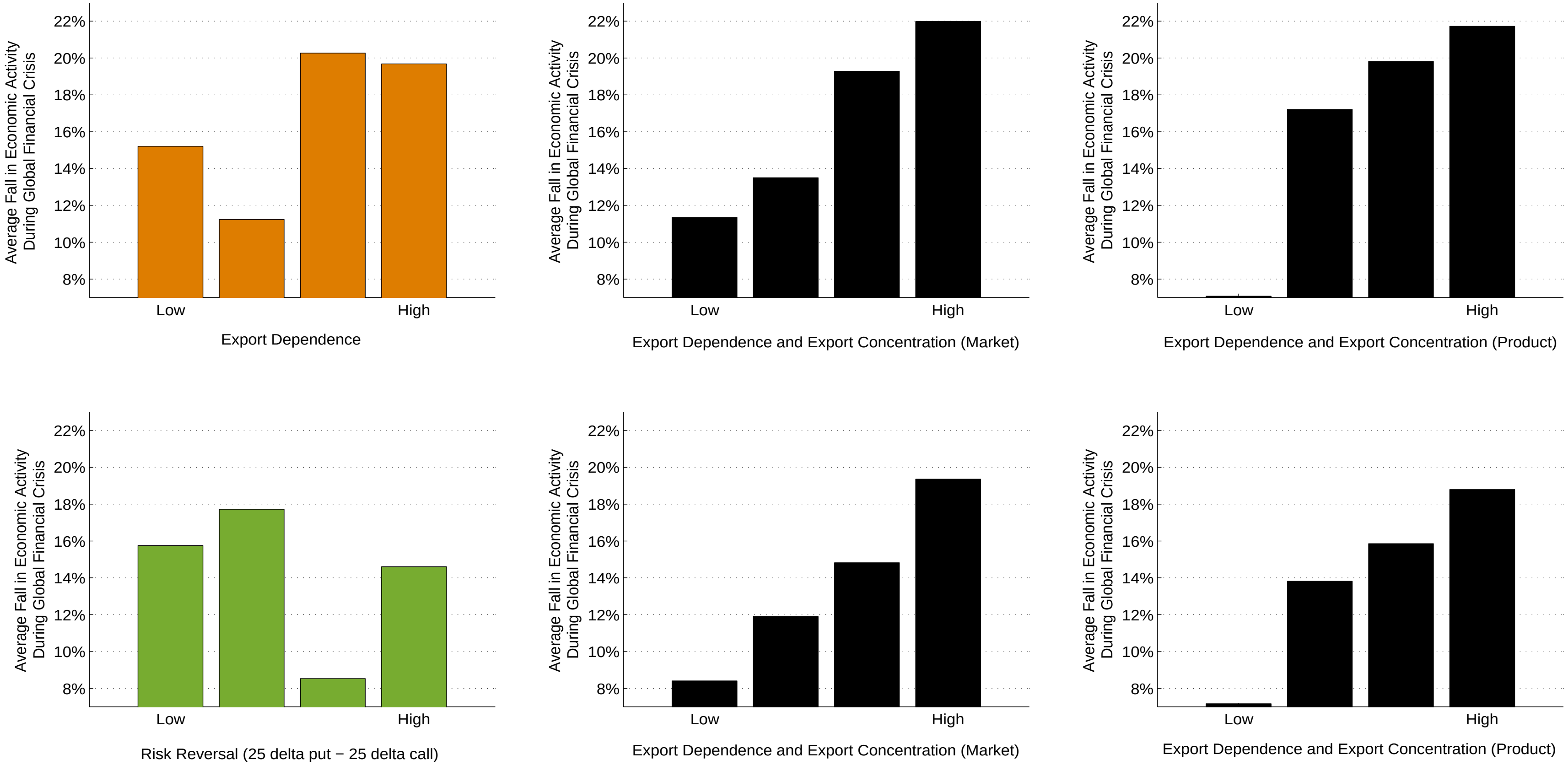



**Figure 2:** ***Export Dependence, Export Concentration, Risk Reversals and the Global Financial Crisis.*** *The figure presents the relationship between export dependence, export concentration, risk reversals and the fall in economic activity during the global financial crisis. In the top-left corner, the bar chart displays the average fall in economic activity, measured as the percentage decline in economic output from the peak (pre-crisis) value of either real GDP or real industrial production to the trough (crisis) level of economic activity, relative to countries' average pre-crisis ratio of exports-to-GDP between 2006 Q2 and 2008 Q2. Countries are divided into quartiles based on the exports-to-GDP ratio. In the top-middle and top-right charts, countries are initially sorted based on their exports-to-GDP ratio as before but are then divided into two equal groups. Within those groups countries are again sorted, based on their export concentration using either the market concentration (top middle) or product concentration (top right). In the lower panel, the bottom-left chart presents the average fall in countries output for four groups of countries sorted by their average risk reversal against the US dollar in August 2008. In the bottom-middle and bottom-right charts, the same method is applied as before, sorting first on export dependence and then on export concentration. The difference is that now only the countries for which risk-reversal data were available are included (35 countries relative to 55 countries previously examined). Data on real GDP, nominal GDP, industrial production and exports are collected from the IMF's International Financial Statistics database except for Venezuela and Kazakhstan, for which industrial production data was collected from National Statistical agencies. Export concentration by country (market) is collected from the IMF's Direction of Trade database and includes monthly bilateral export data for 215 countries from 1983 to 2011. Export concentration by product is collected from the United Nations Conference on Trade and Development (UNCTAD). UNCTAD's database on merchandize exports by product is recorded yearly from 1995 onwards and includes data on the dollar value of exports for 255 different products. Data on risk reversals are over-the-counter quotes from JP Morgan, kindly provided by Pasquale Della Corte.* *[Go to page 15].*

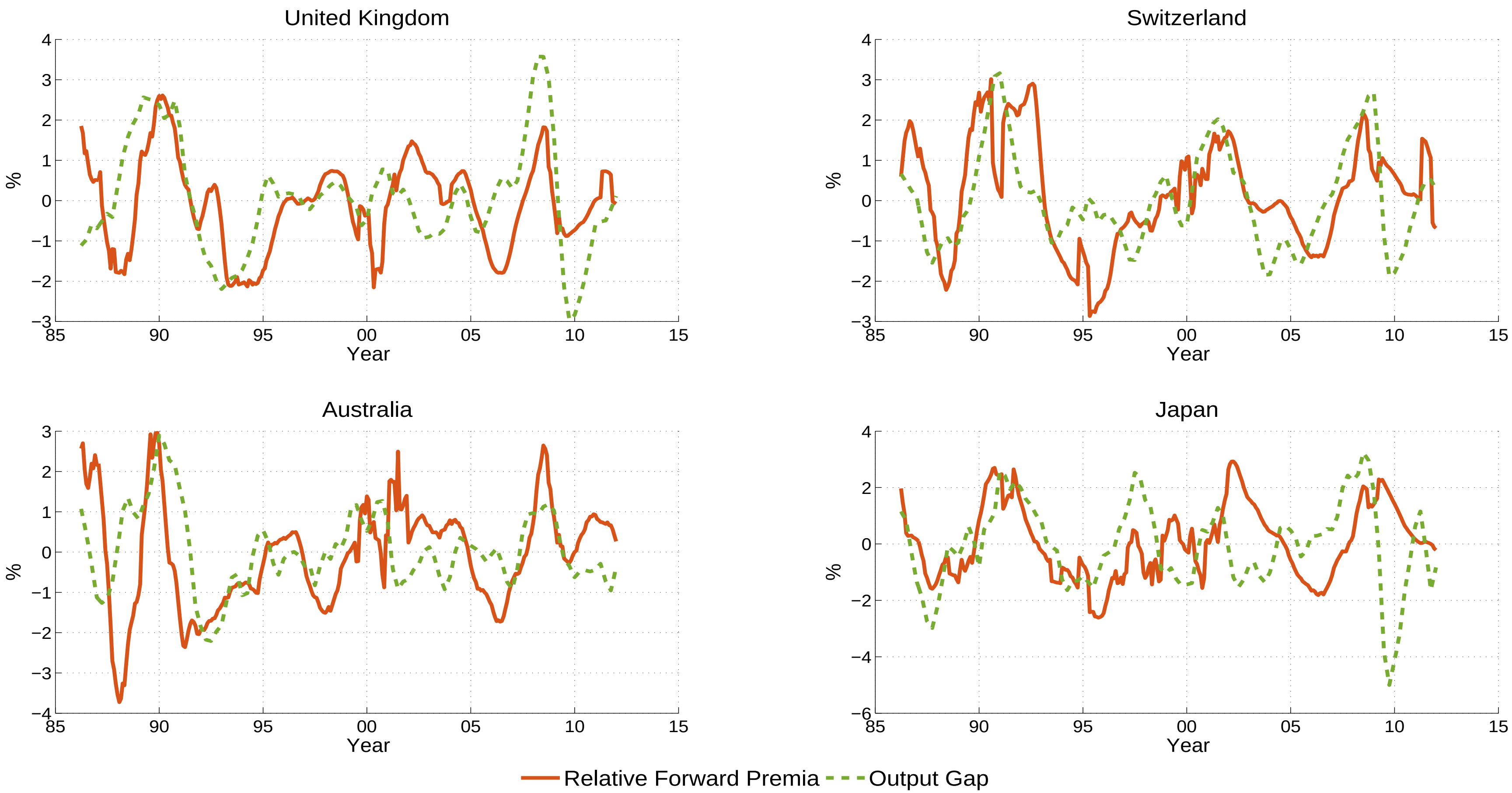



**Figure 3:** ***The Output Gap and Relative Forward Premia in Four Advanced Economies.*** *The figure presents the relationship between a country's output gap and relative forward premia between 1985 and 2011 for four advanced economies, the UK, Switzerland, Australia and Japan. The output gap is measured as the deviation of real GDP from the trend in GDP, estimated using a Hodrick-Prescott filter. In the figure the quarterly output gap is converted to a monthly series by holding the output gap constant until a new observation is available. To smooth the series, I plot the average value over the previous six months. The forward-premia is calculated as the difference between the forward and spot exchange rates at time t, scaled by the time-t spot rate. Forward and spot exchange rates are collected with respect to the US dollar. To calculate the relative forward-premia, I calculate the difference between the forward premia at time t and the average forward premia over the past two years. Data on nominal GDP and the GDP deflator are collected from the IMF's* International Financial Statistics *database. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 17].*

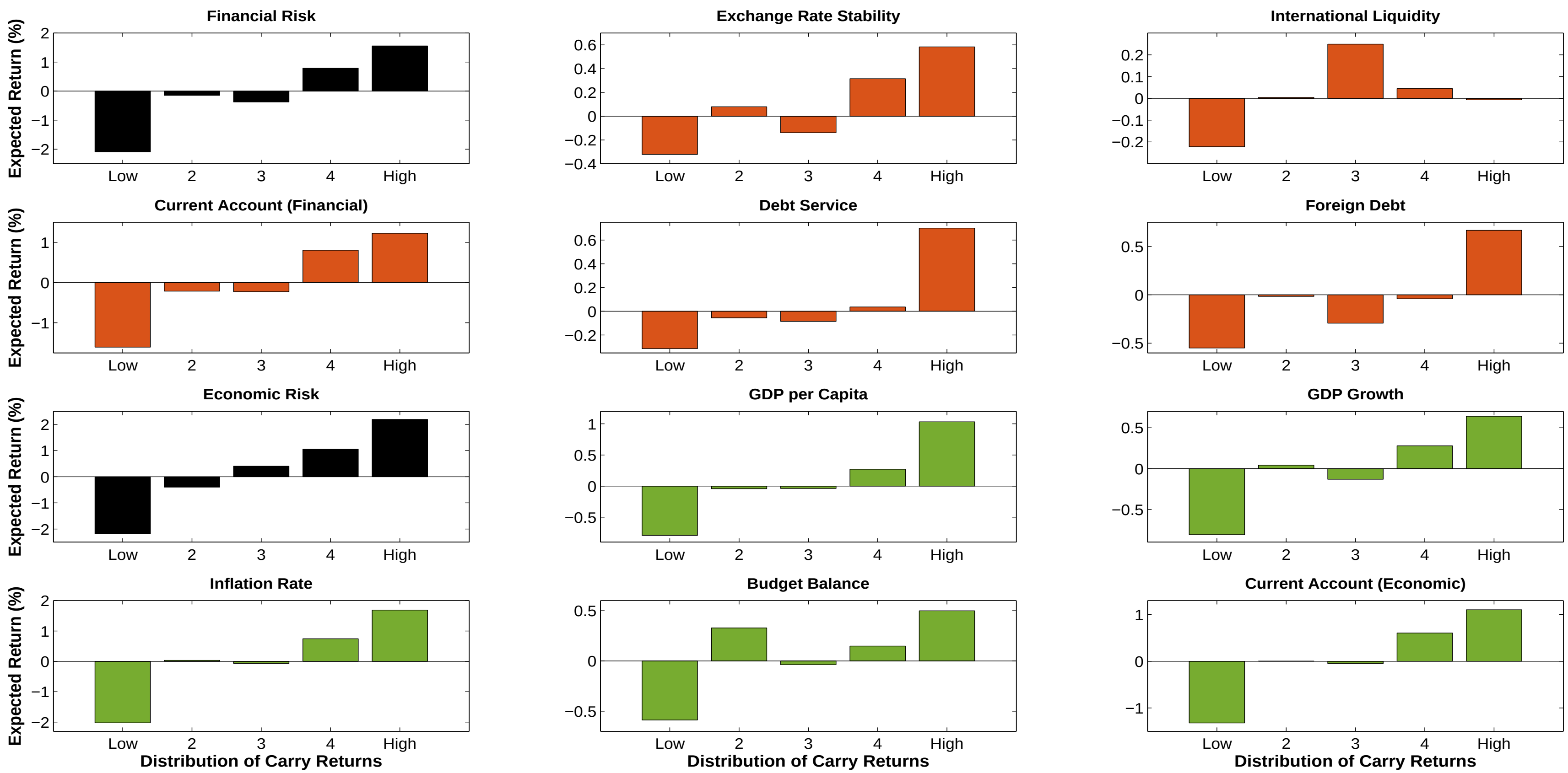



**Figure 4:** ***Conditional Excess Currency Returns of Financial and Macroeconomic Characteristics.*** *The figure presents the average return to portfolios sorted based on different financial and macroeconomic characteristics of countries, conditional on the return to the currency carry trade. The portfolios in question are High-Minus-Low (HML) style portfolios, in which the returns to the lowest risk portfolio are subtracted from those of the highest risk portfolio. The average returns are then calculated for each of these portfolios conditional on the quintile of the currency carry trade return. For example, if the characteristic generates high returns when the currency carry trade performs well, and low returns when the currency carry trade performs badly, then we observe a monotonic spread in returns from Low to High, as is the case for aggregate Economic Risk. Data on the country characteristics are collected from the PRS's International Country Risk Guide database between 1983 and 2011. The currency carry trade is calculated using data on 55 currencies by sorting currencies each month into portfolios, based on their forward premia relative to the US dollar. The carry trade is calculated as the difference in returns on the highest and lowest forward premia sorted currency portfolios. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 22].*

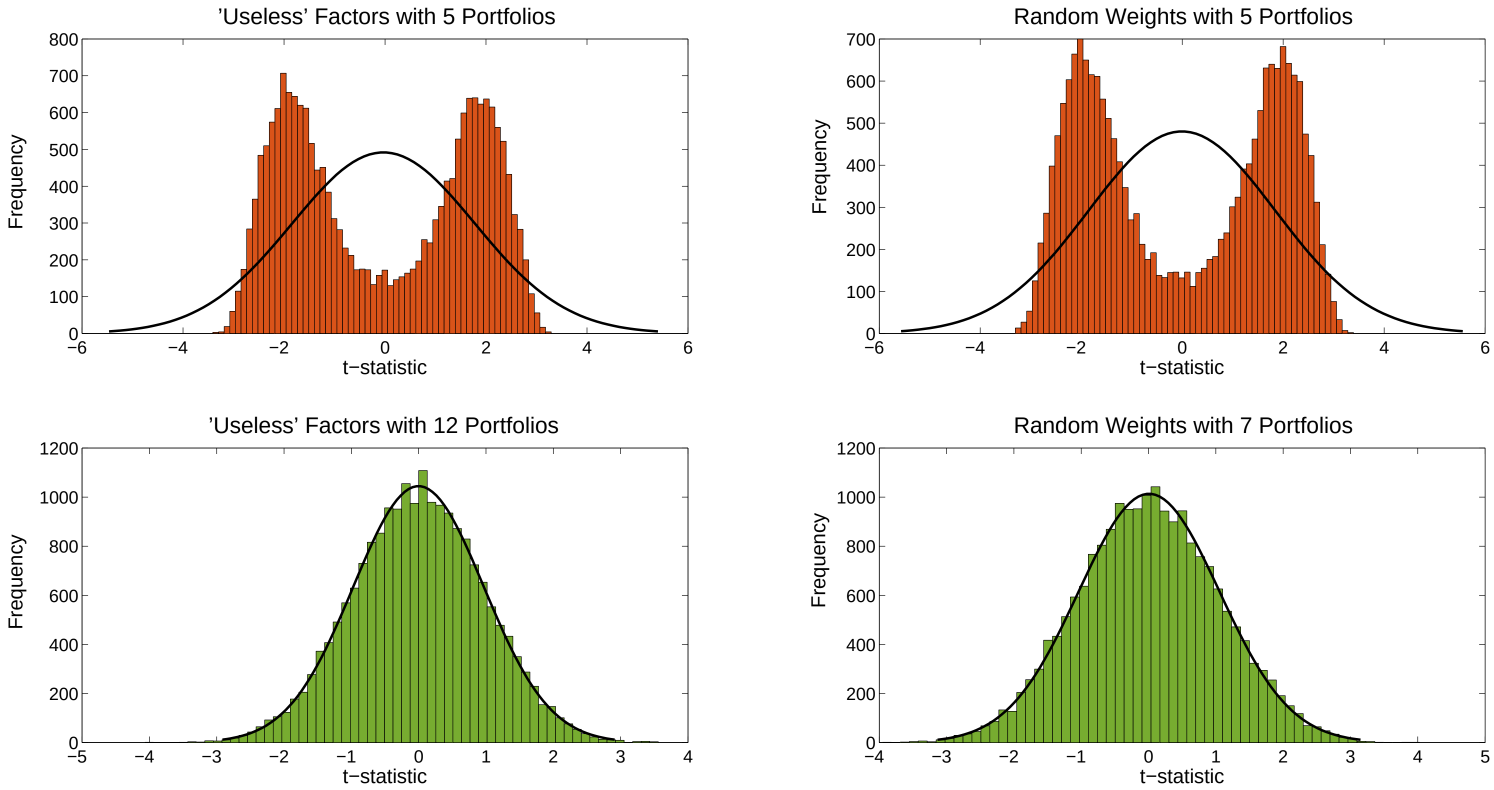



**Figure 5:** ***The Distribution of Simulated t-statistics.*** *The figure presents histograms of simulated t-statistics when pricing test asset portfolios using artificially constructed factors. In the top-left corner the histogram is constructed by simulating 20,000 factors by randomly assigning currencies from the All Countries sample to one of five portfolios each month. The factors are constructed by taking the difference in returns on the fifth and first portfolios. The test asset portfolios are five currency portfolios sorted on the basis of the forward premia. High interest currencies are included in the fifth portfolio, while low interest currencies are included in the first portfolio. The t-statistics are based on the factor price of risk of the simulated factor, estimated using the Fama-MacBeth procedure, when pricing the five forward-premia-sorted portfolios, in addition to the DOL risk factor. In the top-right figure, the 20,000 factors are constructed by creating a dollar-neutral portfolio by randomly allocating weights to each of the five forward-premia-sorted portfolios each month. The factors are re-scaled such that they are always long and short one dollar. In the bottom two figures, while the factors remain the same, more test asset portfolios are included. In the bottom-right figure, both factors (DOL and HML) are included, as well as the five randomly constructed portfolios. In the bottom-right figure, only the two risk factors are added to the five forward-premia-sorted portfolios. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 24].*

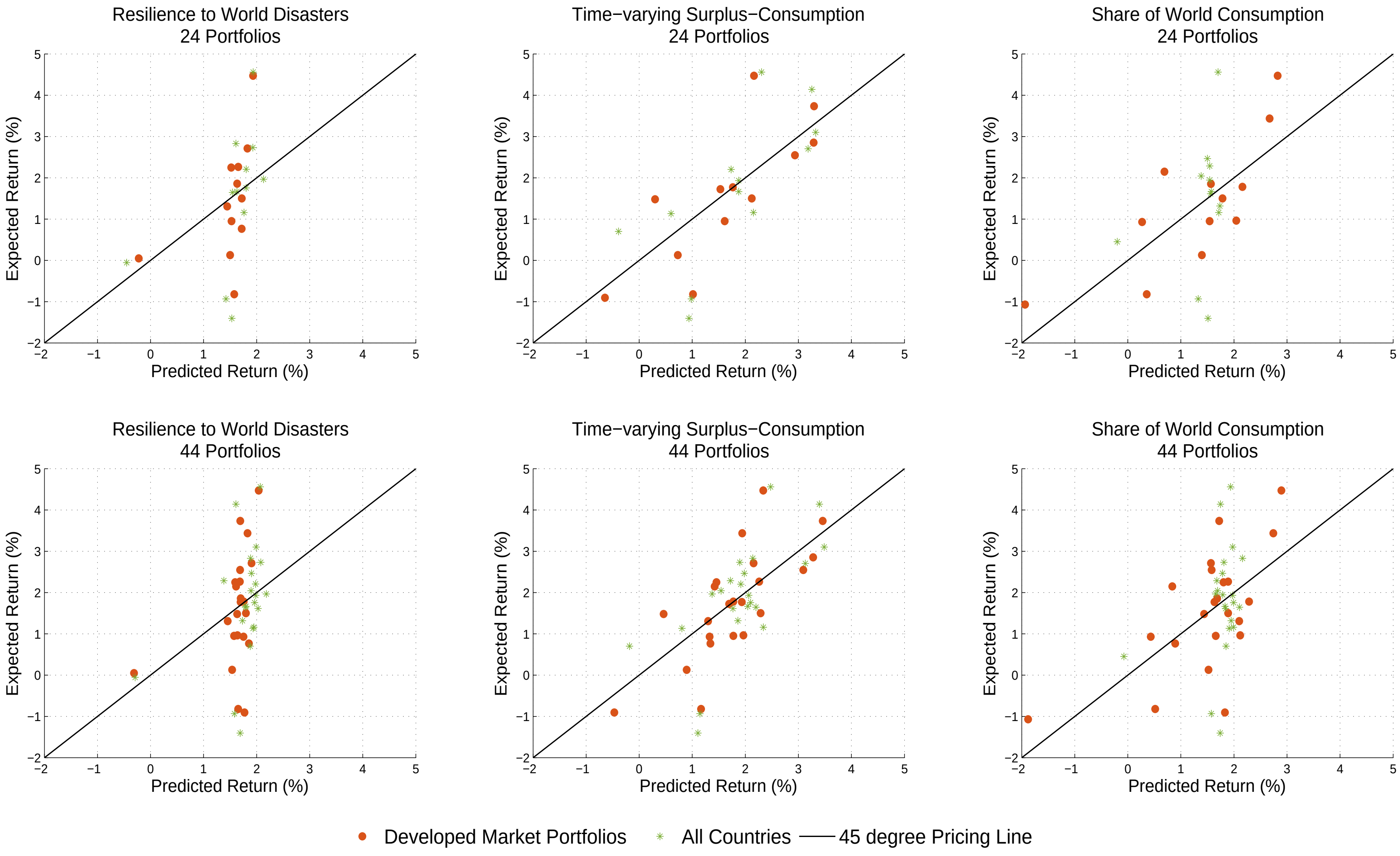



**Figure 6:** ***Pricing Errors for the Three Theory-Driven Factors.*** *The figure presents the pricing errors from cross-sectional asset pricing tests for both the All Countries and Developed Countries samples. In the left-hand two figures, the factor represents countries' resilience to world disasters. In the middle two figures, the factor reflects countries' time-varying surplus-consumption ratio, while in the right-hand two figures the factor represents countries' share of world consumption. Pricing errors are calculated by first estimating the predicted rate of return on portfolios using the Fama-MacBeth asset pricing procedure, and then by comparing the return with the historical average for the test asset portfolios. In the top panel of figures, the test asset are five forward-premia-sorted portfolios, two return-based risk factors and five portfolios sorted by the characteristic under investigation. In the lower three panels, the test asset portfolios also include the five portfolios sorted by the other two theory-driven characteristics. Details on the data underlying all the theory-driven factors can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 28].*

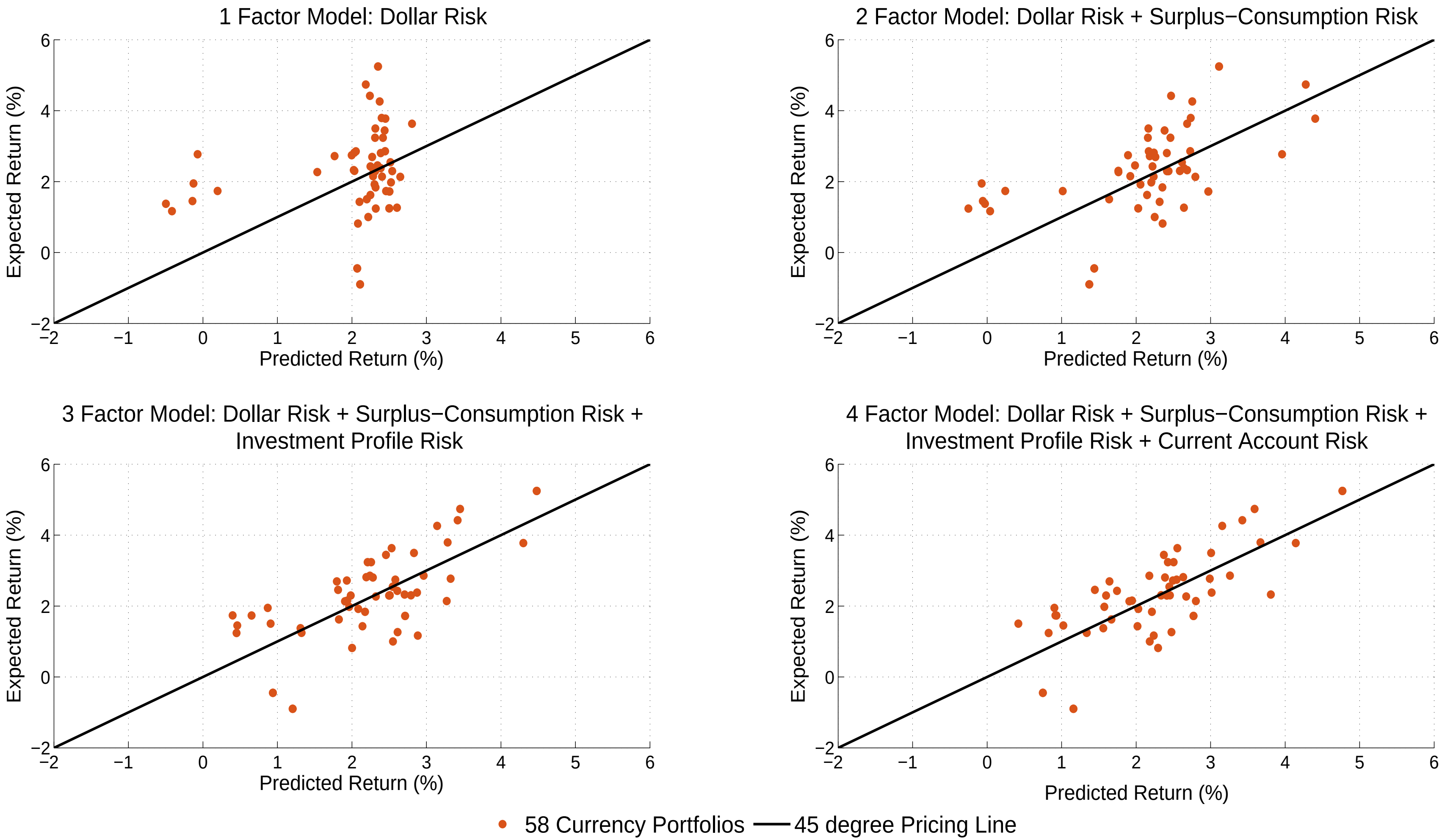



**Figure 7:** ***Incremental Pricing Errors with Additional Characteristic Factors.*** *The figure presents pricing errors for 58 test assets portfolios described in Section 6. The figure in the top-left corner includes only DOL risk as a pricing factor, in the top-right figure the surplus-consumption factor is added to DOL risk. In the bottom-left figure, the model includes three-factors with the addition of the Investment Profile factor. Finally, the pricing errors from the four factor model are presented in the bottom-right figure, following the inclusion of the Current Account factor. Pricing errors are calculated by first estimating the predicted rate of return on portfolios using the Fama-MacBeth asset pricing procedure, and the by comparing the return with the historical average for the test asset portfolios. Details of the data on the theory driven and alternative characteristic factors can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 34].*

| | Panel A: All Countries | | | | | | | Panel B: Developed Countries | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **P1** | **P2** | **P3** | **P4** | **P5** | ***DOL*** | ***HML*** | **P1** | **P2** | **P3** | **P4** | **P5** | ***DOL*** | ***HML*** |
| ***Sort: Forward Premia*** | | | | | | | | | | | | | | |
| *Mean (%)* | -1.79 | -0.69 | 2.66 | 2.37 | 6.53 | 1.82 | 8.32 | -1.46 | 0.76 | 1.66 | 2.33 | 5.61 | 1.78 | 7.08 |
| *Med (%)* | -1.02 | 1.99 | 3.27 | 4.02 | 9.30 | 3.46 | 11.51 | -2.18 | 2.96 | 4.25 | 3.89 | 6.94 | 3.20 | 11.12 |
| *Sdev (%)* | 7.86 | 7.93 | 8.19 | 8.92 | 9.76 | 7.41 | 8.88 | 10.10 | 9.82 | 9.42 | 9.78 | 11.41 | 8.82 | 11.04 |
| *Skew* | -0.07 | -0.62 | -0.44 | -0.90 | -0.79 | -0.57 | -1.02 | 0.16 | -0.21 | -0.35 | -0.75 | -0.51 | -0.33 | -1.13 |
| *Kurt* | 4.17 | 5.26 | 4.44 | 6.30 | 5.66 | 4.45 | 5.25 | 3.52 | 3.70 | 4.41 | 5.74 | 4.82 | 3.79 | 6.07 |
| $AC_1$ | 0.03 | 0.05 | 0.09 | 0.08 | 0.19 | 0.10 | 0.14 | 0.02 | 0.08 | 0.10 | 0.07 | 0.14 | 0.09 | 0.09 |
| *SR* | -0.23 | -0.09 | 0.32 | 0.27 | 0.67 | 0.24 | 0.94 | -0.15 | 0.08 | 0.18 | 0.24 | 0.49 | 0.20 | 0.64 |
| *MDD (%)* | -38.9 | -38.0 | -32.9 | -33.1 | -33.1 | -24.6 | -27.1 | -46.8 | -45.9 | -38.0 | -32.4 | -35.7 | -36.9 | -38.9 |
| ***Sort: Resilience to World Disasters*** | | | | | | | | | | | | | | |
| *Mean (%)* | 1.96 | 2.73 | 1.75 | 1.76 | 2.82 | 2.21 | 0.86 | 0.76 | 2.71 | 2.25 | 1.31 | 2.26 | 1.86 | 1.50 |
| *Med (%)* | 3.14 | 5.09 | 4.14 | 2.81 | 5.10 | 3.75 | -0.22 | 0.47 | 5.65 | 4.53 | 1.76 | 3.15 | 3.47 | 1.84 |
| *Sdev (%)* | 8.78 | 8.84 | 8.87 | 9.43 | 10.13 | 8.04 | 8.74 | 8.83 | 10.30 | 9.03 | 10.29 | 10.85 | 8.71 | 8.67 |
| *Skew* | -0.80 | -0.56 | -1.03 | -0.38 | -0.45 | -0.54 | 0.53 | -0.01 | -0.54 | -0.56 | -0.33 | -0.30 | -0.37 | -0.15 |
| *Kurt* | 6.90 | 4.75 | 7.29 | 4.61 | 4.94 | 4.34 | 5.86 | 3.82 | 4.47 | 5.73 | 4.46 | 4.06 | 3.89 | 3.95 |
| $AC_1$ | 0.13 | 0.10 | 0.10 | 0.05 | 0.09 | 0.10 | 0.04 | 0.08 | 0.06 | 0.10 | 0.07 | 0.01 | 0.08 | -0.01 |
| *SR* | 0.22 | 0.31 | 0.20 | 0.19 | 0.28 | 0.27 | 0.10 | 0.09 | 0.26 | 0.25 | 0.13 | 0.21 | 0.21 | 0.17 |
| *MDD (%)* | -64.8 | -30.9 | -33.0 | -37.0 | -31.6 | -25.6 | -29.3 | -49.2 | -37.9 | -33.7 | -40.2 | -35.6 | -36.3 | -20.2 |
| ***Sort: Time-Varying Surplus-Consumption Ratio*** | | | | | | | | | | | | | | |
| *Mean (%)* | 0.70 | 1.13 | 1.93 | 3.10 | 4.14 | 2.20 | 3.44 | -0.91 | 1.48 | 1.77 | 2.55 | 3.73 | 1.72 | 4.64 |
| *Med (%)* | 2.98 | 2.56 | 4.01 | 4.71 | 5.77 | 4.10 | 2.54 | 2.38 | 2.98 | 2.74 | 2.90 | 5.09 | 3.47 | 2.84 |
| *Sdev (%)* | 8.98 | 8.87 | 8.79 | 9.08 | 8.42 | 7.76 | 7.92 | 10.86 | 9.57 | 9.84 | 9.41 | 9.81 | 8.79 | 8.26 |
| *Skew* | -0.20 | -0.36 | -0.44 | -0.95 | -1.02 | -0.63 | -0.07 | -0.69 | -0.27 | -0.18 | -0.14 | -0.50 | -0.38 | 0.76 |
| *Kurt* | 3.88 | 3.98 | 4.48 | 7.50 | 7.23 | 4.78 | 4.34 | 5.10 | 3.47 | 4.12 | 3.65 | 5.32 | 3.82 | 5.11 |
| $AC_1$ | 0.16 | 0.02 | 0.07 | 0.11 | 0.10 | 0.10 | 0.10 | 0.13 | 0.02 | 0.06 | 0.09 | 0.06 | 0.08 | -0.01 |
| *SR* | 0.08 | 0.13 | 0.22 | 0.34 | 0.49 | 0.28 | 0.43 | -0.08 | 0.15 | 0.18 | 0.27 | 0.38 | 0.20 | 0.56 |
| *MDD (%)* | -55.1 | -32.3 | -36.4 | -34.7 | -28.2 | -23.6 | -32.7 | -47.7 | -36.6 | -47.7 | -46.0 | -27.6 | -35.9 | -20.5 |
| ***Sort: Share of World Consumption*** | | | | | | | | | | | | | | |
| *Mean (%)* | 2.29 | 1.32 | 1.61 | 2.46 | 2.04 | 1.94 | -0.24 | 3.44 | 1.78 | 0.96 | 2.15 | 0.93 | 1.85 | -2.51 |
| *Med (%)* | 3.18 | 3.93 | 2.94 | 4.62 | 2.09 | 3.49 | -1.55 | 6.08 | 3.56 | 3.01 | 3.07 | 1.47 | 3.33 | -5.00 |
| *Sdev (%)* | 7.53 | 8.38 | 8.62 | 8.40 | 8.55 | 7.28 | 7.34 | 10.12 | 11.24 | 8.97 | 9.44 | 9.63 | 8.82 | 8.04 |
| *Skew* | -0.37 | -0.95 | -0.57 | -0.98 | -0.23 | -0.56 | 0.19 | -0.48 | -0.32 | -0.48 | -0.51 | -0.02 | -0.35 | 0.67 |
| *Kurt* | 6.65 | 6.87 | 4.92 | 7.12 | 4.26 | 4.48 | 4.54 | 4.75 | 3.51 | 5.73 | 5.30 | 3.34 | 3.78 | 4.62 |
| $AC_1$ | 0.10 | 0.04 | 0.12 | 0.11 | 0.06 | 0.10 | 0.03 | 0.06 | 0.10 | 0.07 | 0.08 | 0.05 | 0.09 | 0.02 |
| *SR* | 0.30 | 0.16 | 0.19 | 0.29 | 0.24 | 0.27 | -0.03 | 0.34 | 0.16 | 0.11 | 0.23 | 0.10 | 0.21 | -0.31 |
| *MDD (%)* | -59.5 | -33.2 | -36.4 | -33.3 | -40.6 | -24.6 | -41.6 | -78.5 | -46.9 | -38.1 | -29.2 | -53.1 | -37.0 | -69.3 |

**Table 1:** ***Summary Statistics for Alternative Sorting Procedures.*** *The table presents summary statistics for both the All Countries and Developed Countries samples. In the top group of summary statistics, currencies are sorted into five portfolios each month on the basis of the currencies' forward premia relative to the US dollar. DOL represents a portfolio constructed by taking the average return across the five sorted portfolios, while HML is constructed by taking the difference in returns on the extreme portfolios ($P5-P1$). I report the mean, median (Med), standard deviation (Sdev), skewness (Skew), kurtosis (Kurt), the $\beta$ coefficient from a regression of portfolio returns on one-period lagged returns ($y_t = \alpha+\beta y_{t-1}+\epsilon_t$), the Sharpe Ratio (SR), calculated as the average monthly return multiplied by 12 and divided by the monthly standard deviation multiplied by the square root of 12. I also report the maximum drawdown (MDD) from investing in each portfolio. The portfolios are sorted in the other three groups based on the theory-driven proxies described in Section 3. Full details of the data used to construct the portfolios can also be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 20].*

**Panel A: Financial Risks**

| | *Fama-MacBeth factor risk prices* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Financial Agg.** | | **FX Stability** | | **Int. Liquidity** | | **Current Account** | | **Debt Service** | | **Foreign Debt** | |
| | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ |
| *Price (%)* | 1.86 | 7.00 | 1.88 | 12.7 | 1.85 | 14.5 | 1.65 | 6.11 | 1.96 | 15.1 | 1.73 | 7.40 |
| *Std. Error* | [1.41] | [2.24] | [1.41] | [4.40] | [1.38] | [5.75] | [1.38] | [2.18] | [1.37] | [5.97] | [1.40] | [2.49] |
| *Mean* | 2.19 | 0.57 | 2.31 | 1.74 | 2.36 | 0.15 | 2.36 | 0.50 | 2.39 | -0.29 | 2.40 | 0.87 |
| | *Cross-section regression statistics* | | | | | | | | | | | |
| $R^2$ (%) | 77.6 | | 91.1 | | 81.2 | | 62.3 | | 81.7 | | 71.0 | |
| $\chi^2$ | 10.7 | | 4.92 | | 7.60 | | 14.5 | | 5.36 | | 11.90 | |
| $p-value$ | (0.01) | | (0.18) | | (0.06) | | (0.00) | | (0.15) | | (0.01) | |
| *RMSPE (%)* | 1.04 | | 0.66 | | 0.96 | | 1.35 | | 0.94 | | 1.19 | |
| $\rho$ (%) | 53.7 | | 24.1 | | 15.8 | | 43.0 | | 12.7 | | 31.5 | |

**Panel B: Macroeconomic Risks**

| | *Fama-MacBeth factor risk prices* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Economic Agg.** | | **GDP per Capita** | | **GDP Growth Rate** | | **Inflation Rate** | | **Budget Balance** | | **Current Account** | |
| | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ |
| *Price (%)* | 1.83 | 4.74 | 1.67 | 5.70 | 1.79 | 10.4 | 1.79 | 5.44 | 1.77 | 11.9 | 1.66 | 7.34 |
| *Std. Error* | [1.42] | [1.52] | [1.37] | [1.81] | [1.39] | [3.73] | [1.40] | [1.73] | [1.39] | [4.21] | [1.38] | [2.31] |
| *Mean* | 2.31 | 1.79 | 2.38 | 1.37 | 2.41 | 0.24 | 2.32 | 1.70 | 2.40 | 1.45 | 2.39 | 1.09 |
| | *Cross-section regression statistics* | | | | | | | | | | | |
| $R^2$ (%) | 71.8 | | 92.0 | | 77.0 | | 82.9 | | 87.3 | | 86.4 | |
| $\chi^2$ | 12.2 | | 4.18 | | 10.25 | | 7.83 | | 6.69 | | 7.04 | |
| $p-value$ | (0.01) | | (0.24) | | (0.02) | | (0.05) | | (0.08) | | (0.07) | |
| *RMSPE (%)* | 1.17 | | 0.62 | | 1.06 | | 0.91 | | 0.79 | | 0.81 | |
| $\rho$ (%) | 63.1 | | 52.1 | | 27.3 | | 59.5 | | 25.6 | | 43.6 | |

**Table 2:** ***Asset Pricing Tests with Financial and Macroeconomic Factors.*** *The table presents cross-sectional asset pricing results from the Fama-MacBeth (FMB) procedure. The test asset portfolios are five currency portfolios sorted monthly by forward premia, relative to the US dollar. The risk factors include DOL risk, the average return across the five forward-premia-sorted portfolios each month, and HML risk. The HML factor is first constructed by sorting currencies into one of five portfolios, on the basis of the implied source of currency risk exposure, using financial- (top group) and macroeconomic-based (bottom group) characteristics. Once the five portfolios are finalized, the factor is constructed as* $[(P5+P4)-(P1+P2)]/2$. *The factor price of risk* $\lambda$ *and standard errors are estimated in the second-step of the FMB procedure, and are reported for both factors. I also report the OLS* $R^2$*, the* $\chi^2$ *test statistic and associated p-value. A p-value greater than 0.05 suggests the null hypothesis, that all pricing errors are jointly equal to zero, cannot be rejected. Root mean squared pricing errors (RMSPE) are also reported, as is the correlation of the HML factor with the second principal component of the forward-premia-sorted portfolios* ($\rho$)*. Finally, I report the average in-sample (mean) return of the two factors. Details on the data used to construct the financial and macroeconomic factors can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 22].*

| Panel A: 5 Forward-Premia-Sorted Test Assets | | | | | | | |
|---|---|---|---|---|---|---|---|
| ***Relationship between simulated factors and the 'true' factor*** | | | | | | | |
| correlation (% >) | **0.05** | **0.10** | **0.30** | **0.50** | **0.70** | **0.90** | **0.95** |
| *'useless' factor* | 57.3 | 24.9 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| *random weights* | 60.6 | 29.6 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 |
| ***Factor price of risk*** | | | | | | | |
| t-statistic (% >) | **0.67** | **1.65** | **1.96** | **2.33** | **2.58** | **2.81** | **3.29** |
| *asymptotic* | 50.0 | 10.0 | 5.0 | 2.0 | 1.0 | 0.5 | 0.1 |
| *'useless' factor (FMB)* | 90.1 | 56.0 | 38.0 | 18.1 | 8.0 | 2.5 | 0.0 |
| *'useless' factor (GMM2)* | 78.5 | 35.6 | 21.2 | 8.2 | 3.1 | 0.9 | 0.0 |
| *random weights (FMB)* | 91.0 | 58.7 | 40.7 | 20.1 | 9.5 | 3.3 | 0.0 |
| *random weights (GMM2)* | 79.4 | 39.0 | 24.7 | 11.4 | 5.1 | 1.5 | 0.0 |
| ***Model fit*** | | | | | | | |
| $R^2$ (% >) | **0.05** | **0.10** | **0.30** | **0.50** | **0.70** | **0.90** | **0.95** |
| *'useless' factor (FMB)* | 93.5 | 80.8 | 56.2 | 37.5 | 19.9 | 4.1 | 1.4 |
| *'useless' factor (GMM2)* | 27.7 | 25.9 | 18.8 | 12.2 | 6.0 | 1.2 | 0.4 |
| *random weights (FMB)* | 96.1 | 82.8 | 59.3 | 41.5 | 24.0 | 5.9 | 2.4 |
| *random weights (GMM2)* | 31.8 | 29.9 | 22.8 | 15.5 | 8.5 | 2.1 | 0.8 |
| ***Pricing errors*** | | | | | | | |
| $\chi^2$ p-value (% <) | **0.05** | **0.10** | **0.30** | **0.50** | **0.70** | **0.90** | **0.95** |
| *'useless' factor (FMB)* | 28.2 | 37.9 | 59.1 | 73.1 | 84.5 | 94.8 | 97.3 |
| *'useless' factor (GMM2)* | 28.6 | 38.2 | 59.5 | 73.4 | 84.7 | 95.1 | 97.5 |
| *random weights (FMB)* | 21.0 | 28.2 | 47.0 | 62.8 | 77.4 | 92.1 | 95.7 |
| *random weights (GMM2)* | 21.1 | 28.5 | 47.4 | 63.1 | 77.6 | 92.2 | 95.9 |

| Panel B: 7 and 12 Test Assets | | | | | | | |
|---|---|---|---|---|---|---|---|
| ***Relationship between simulated factors and the 'true' factor*** | | | | | | | |
| correlation (% >) | **0.05** | **0.10** | **0.30** | **0.50** | **0.70** | **0.90** | **0.95** |
| *'useless' factor* | 57.3 | 24.9 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| *random weights* | 59.5 | 29.3 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 |
| ***Factor price of risk*** | | | | | | | |
| t-statistic (% >) | **0.67** | **1.65** | **1.96** | **2.33** | **2.58** | **2.81** | **3.29** |
| *asymptotic* | 50.0 | 10.0 | 5.0 | 2.0 | 1.0 | 0.5 | 0.1 |
| *'useless' factor (FMB)* | 49.2 | 8.9 | 4.3 | 1.5 | 0.6 | 0.3 | 0.1 |
| *'useless' factor (GMM2)* | 34.1 | 1.8 | 0.5 | 0.1 | 0.0 | 0.0 | 0.0 |
| *random weights (FMB)* | 52.6 | 12.0 | 6.1 | 2.5 | 1.3 | 0.6 | 0.1 |
| *random weights (GMM2)* | 34.1 | 1.9 | 0.5 | 0.1 | 0.0 | 0.0 | 0.0 |
| ***Model fit*** | | | | | | | |
| $R^2$ (% >) | **0.05** | **0.10** | **0.30** | **0.50** | **0.70** | **0.90** | **0.95** |
| *'useless' factor (FMB)* | 93.2 | 68.5 | 9.8 | 0.5 | 0.0 | 0.0 | 0.0 |
| *'useless' factor (GMM2)* | 14.5 | 9.7 | 1.2 | 0.0 | 0.0 | 0.0 | 0.0 |
| *random weights (FMB)* | 83.7 | 52.8 | 2.3 | 0.0 | 0.0 | 0.0 | 0.0 |
| *random weights (GMM2)* | 0.6 | 0.3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ***Pricing errors*** | | | | | | | |
| $\chi^2$ p-value (% <) | **0.05** | **0.10** | **0.30** | **0.50** | **0.70** | **0.90** | **0.95** |
| *'useless' factor (FMB)* | 99.2 | 99.4 | 99.5 | 99.6 | 99.7 | 99.8 | 99.8 |
| *'useless' factor (GMM2)* | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| *random weights (FMB)* | 91.1 | 93.7 | 95.7 | 96.5 | 96.9 | 97.3 | 97.4 |
| *random weights (GMM2)* | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

**Table 3:** ***Asset Pricing with Simulated Factors.*** *The table presents simulated cross-sectional asset pricing statistics from the Fama-MacBeth and GMM procedures, using artificially constructed 'risk factors'. In Panel A, the test asset portfolios are five currency portfolios sorted monthly by forward premia, relative to the US dollar. The risk factors include DOL risk, the average return across the five forward-premia-sorted portfolio each month, and HML risk. The HML factor is constructed in one of two ways. The first method involves constructing a factor by randomly sorting currencies into one of five portfolios each month, and then forming the factor as the difference between the returns on the extreme portfolios ($P5 - P1$). I construct 20,000 factors in this manner and refer to this group as 'useless' factors. The second method involves constructing a dollar neutral portfolio by randomly assigning portfolio weights to each of the five forward-premia-sorted portfolios each month. The portfolios are then re-scaled such that the portfolio is exactly long and short one dollar each month. Once again, I simulate 20,000 factors in this way and label the group 'random weight' factors. I report the proportion of randomly generated factors which have a correlation with the 'Slope' factor ($P5 - P1$, for the forward-premia-sorted portfolios) over given thresholds, generate a t-statistic in cross-sectional regressions in excess of well-defined critical values, can explain particular levels of cross-sectional return variation (FMB and GMM2 $R^2$ statistics) or are unable to 'price' all the test asset portfolios (p-values from the $\chi^2$ test, in which the null hypothesis is that all pricing errors are jointly equal to zero). In Panel B, I expand the number of test assets. In the case of the 'random weight' factors, I also include the DOL and HML factors as test portfolios. In the case of 'useless' factors, I also include the five randomly constructed portfolios to take the number of test asset portfolio up to 12. Details of the FMB and GMM procedures can be found in Section 2. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 24].*

**Panel A: 12 Portfolios**

| | Resilience to World Disasters | | | | Time-varying Surplus-Consumption | | | | Share of World Consumption | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ |
| *GMM1* | 0.28 | -0.26 | 1.80 | -0.45 | 0.27 | 0.89 | 1.73 | 3.18 | 0.27 | -0.19 | 1.54 | -0.20 |
| *Std. Error* | (0.24) | (0.34) | (2.15) | (1.41) | (0.26) | (0.35) | (2.09) | (1.49) | (0.26) | (0.40) | (1.94) | (1.15) |
| *GMM2* | 0.34 | -0.40 | 2.21 | -0.05 | 0.27 | 0.87 | 2.20 | 2.70 | 0.27 | -0.30 | 1.94 | 0.45 |
| *Std. Error* | (0.24) | (0.33) | (2.15) | (1.39) | (0.25) | (0.34) | (2.08) | (1.48) | (0.25) | (0.38) | (1.94) | (1.13) |
| *FMB* | | | 1.80 | -0.45 | | | 1.73 | 3.18 | | | 1.54 | -0.20 |
| *Std. Error* | | | (1.51) | (1.00) | | | (1.47) | (1.06) | | | (1.37) | (0.82) |
| *Mean* | | | [2.21] | [-0.05] | | | [2.20] | [2.70] | | | [1.95] | [0.45] |

*Cross-sectional regression statistics*

| | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *GMM1* | 3.7% | 29.8 | 1.41% | -21.3% | 38.0% | 40.3 | 1.23% | 21.9% | -12.2% | 68.9 | 1.44% | -17.1% |
| | (0.00) | (0.00) | | | (0.00) | (0.00) | | | (0.00) | (0.00) | | |
| *GMM2* | -4.3% | 42.9 | 1.47% | | 28.5% | 38.9 | 1.32% | | -24.7% | 77.3 | 1.52% | |
| | (0.00) | (0.00) | | | (0.00) | (0.00) | | | (0.00) | (0.00) | | |
| *FMB* | 21.2% | 85.8 | 1.41% | | 49.2% | 73.8 | 1.23% | | 8.2% | 281.8 | 1.44% | |
| | (0.00) | (0.00) | | | (0.00) | (0.00) | | | (0.00) | (0.00) | | |

**Panel B: 22 Portfolios**

| | Resilience to World Disasters | | | | Time-varying Surplus-Consumption | | | | Share of World Consumption | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ |
| *FMB* | 0.30 | -0.22 | 1.98 | -0.29 | 0.29 | 0.88 | 1.91 | 3.13 | 0.30 | -0.15 | 1.78 | -0.07 |
| *Std. Error* | (0.25) | (0.35) | (2.15) | (1.41) | (0.26) | (0.36) | (2.09) | (1.50) | (0.27) | (0.42) | (1.94) | (1.17) |
| *GMM1* | 0.37 | -0.33 | 2.21 | -0.05 | 0.33 | 1.27 | 2.20 | 2.70 | 0.36 | -0.30 | 1.95 | 0.45 |
| *Std. Error* | (0.24) | (0.34) | (2.15) | (1.39) | (0.24) | (0.32) | (2.08) | (1.48) | (0.26) | (0.39) | (1.94) | (1.13) |
| *GMM2* | | | 1.98 | -0.29 | | | 1.91 | 3.13 | | | 1.78 | -0.07 |
| *Std. Error* | | | (1.51) | (1.00) | | | (1.47) | (1.07) | | | (1.37) | (0.84) |
| *Mean* | | | [2.21] | [-0.05] | | | [2.20] | [2.70] | | | [1.95] | [0.45] |

*Cross-sectional regression statistics*

| | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *GMM1* | 4.9% | 81.2 | 1.27% | -21.3% | 38.2% | 91.2 | 0.99% | 21.9% | -1.1% | 77.0 | 1.28% | -17.1% |
| | (0.00) | (0.00) | | | (0.00) | (0.00) | | | (0.00) | (0.00) | | |
| *GMM2* | 1.9% | 79.3 | 1.29% | | 32.3% | 77.1 | 1.03% | | -4.9% | 79.3 | 1.30% | |
| | (0.00) | (0.00) | | | (0.00) | (0.00) | | | (0.73) | (0.00) | | |
| *FMB* | 13.9% | 375.2% | 1.27% | | 44.1% | 362.0 | 0.99% | | 8.6% | 369.4 | 1.28% | |
| | (0.00) | (3.00) | | | (0.00) | (0.00) | | | (0.73) | (0.00) | | |

**Table 4:** ***Cross-Sectional Asset Pricing Tests: All Countries.*** *The table presents asset pricing results for the All Countries sample. The pricing performance of three theory-driven factors is evaluated using both the Fama-MacBeth (FMB) procedure as well as a Generalized Method of Moments (GMM) estimation. In GMM1, I use an identity matrix as the weighting matrix, while in GMM2 the weighting matrix is an optimal matrix to maximize estimation efficiency. The three factors are HML style factors, constructed to proxy for the theory-driven predictions for currency risk exposure: resilience to world disasters, time-varying surplus-consumption ratio and the share of world consumption. I report factor prices of risk $\lambda$ and estimated b's from the Stochastic Discount Factor, with associated Shanken (1992) and Newey-West (1987) corrected standard errors. Goodness-of-fit statistics include the OLS $R^2$ from the FMB procedure, the OLS adj-$R^2$ from GMM1 and the GLS adj-$R^2$ from GMM2. The $\chi^2$ test statistic is used to measure the degree of portfolio mispricing. The p-value (reported in parentheses) is for the null hypothesis that all portfolios are jointly 'priced', in that the pricing errors are not statistically different from zero. I also report the root mean squared pricing errors (RMSPE) and correlation of the HML factor with the second principal component of five forward-premia-sorted portfolios ($\rho$). In Panel A, 12 test asset portfolios are used in the investigation, including the pricing factors themselves. In Panel B, the number of test assets is expanded to 22. Full details on the formation of the test portfolios and pricing factors, as well as the data used in their construction, can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 25].*

**Panel A: 12 Portfolios**

| | Resilience to World Disasters | | | | Time-varying Surplus-Consumption | | | | Share of World Consumption | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ |
| *FMB* | 0.22 | -0.22 | 1.63 | -0.22 | 0.22 | 0.93 | 1.53 | 3.29 | 0.00 | -0.61 | 1.57 | -1.94 |
| *Std. Error* | (0.22) | (0.38) | (2.33) | (1.32) | (0.21) | (0.27) | (2.36) | (1.50) | (0.21) | (0.42) | (2.36) | (1.41) |
| *GMM1* | 0.31 | -0.16 | 1.85 | 0.05 | 0.24 | 0.94 | 1.72 | 2.85 | 0.12 | -0.63 | 1.85 | -1.07 |
| *Std. Error* | (0.21) | (0.36) | (2.32) | (1.29) | (0.20) | (0.26) | (2.36) | (1.48) | (0.21) | (0.35) | (2.36) | (1.34) |
| *GMM2* | | | 1.63 | -0.22 | | | 1.53 | 3.29 | | | 1.57 | -1.94 |
| *Std. Error* | | | (1.63) | (0.94) | | | (1.66) | (1.08) | | | (1.65) | (1.03) |
| *Mean* | | | [1.86] | [0.05] | | | [1.72] | [2.85] | | | [1.85] | [-1.07] |

*Cross-sectional regression statistics*

| | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *GMM1* | 3.6% | 31.3 | 1.20% | -15.2% | 51.6% | 32.8 | 1.00% | 19.9% | 49.7% | 77.7 | 0.98% | -52.5% |
| | (0.00) | (0.00) | | | (0.00) | (0.00) | | | (0.00) | (0.00) | | |
| *GMM2* | -0.7% | 31.3 | 1.22% | | 48.2% | 30.2 | 1.03% | | 34.5% | 61.9 | 1.11% | |
| | (0.00) | (0.00) | | | (0.00) | (0.00) | | | (0.00) | (0.00) | | |
| *FMB* | 21.1% | 45.4 | 1.20% | | 60.4% | 45.5 | 1.00% | | 58.8% | 157.4 | 0.98% | |
| | (0.00) | (0.00) | | | (0.73) | (0.00) | | | (0.00) | (0.00) | | |

**Panel B: 22 Portfolios**

| | Resilience to World Disasters | | | | Time-varying Surplus-Consumption | | | | Share of World Consumption | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ |
| *FMB* | 0.24 | -0.26 | 1.70 | -0.31 | 0.24 | 0.93 | 1.70 | 3.28 | 0.00 | -0.58 | 1.68 | -1.88 |
| *Std. Error* | (0.22) | (0.39) | (2.33) | (1.33) | (0.21) | (0.28) | (2.36) | (1.51) | (0.21) | (0.44) | (2.36) | (1.41) |
| *GMM1* | 0.29 | -0.18 | 1.86 | 0.05 | 0.31 | 1.05 | 1.72 | 2.85 | 0.12 | -0.72 | 1.85 | -1.07 |
| *Std. Error* | (0.22) | (0.37) | (2.32) | (1.29) | (0.20) | (0.26) | (2.36) | (1.48) | (0.21) | (0.36) | (2.35) | (1.34) |
| *GMM2* | | | 1.70 | -0.31 | | | 1.70 | 3.28 | | | 1.68 | -1.88 |
| *Std. Error* | | | (1.63) | (0.95) | | | (1.66) | (1.09) | | | (1.65) | (1.03) |
| *Mean* | | | [1.86] | [0.05] | | | [1.72] | [2.85] | | | [1.85] | [-1.07] |

*Cross-sectional regression statistics*

| | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ | $R^2$ | $\chi^2$ | $RMSPE$ | $\rho$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *GMM1* | 3.9% | 60.0 | 1.23% | -15.2% | 48.3% | 63.9 | 0.89% | 19.9% | 32.3% | 83.6 | 1.09% | -52.5% |
| | (0.00) | (3.37) | | | (0.00) | (0.00) | | | (0.00) | (0.00) | | |
| *GMM2* | 1.2% | 63.5 | 1.25% | | 47.0% | 60.9 | 0.90% | | 24.8% | 62.9 | 1.15% | |
| | (0.00) | (3.37) | | | (0.00) | (0.00) | | | (0.00) | (0.00) | | |
| *FMB* | 13.1% | 182.6 | 1.23% | | 53.2% | 174.8 | 0.89% | | 38.8% | 182.1 | 1.09% | |
| | (0.00) | (3.37) | | | (0.00) | (0.00) | | | (0.00) | (0.00) | | |

**Table 5:** ***Cross-Sectional Asset Pricing Tests: Developed Countries.*** *The table presents asset pricing results for the Developed Countries sample. The pricing performance of three theory-driven factors is evaluated using both the Fama-MacBeth (FMB) procedure as well as a Generalized Method of Moments (GMM) estimation. In GMM1, I use an identity matrix as the weighting matrix, while in GMM2 the weighting matrix is an optimal matrix to maximize estimation efficiency. The three factors are HML style factors, constructed to proxy for the theory-driven predictions for currency risk exposure: resilience to world disasters, time-varying surplus-consumption ratio and the share of world consumption. I report factor prices of risk* $\lambda$ *and estimated b's from the Stochastic Discount Factor, with associated Shanken (1992) and Newey-West (1987) corrected standard errors. Goodness-of-fit statistics include the OLS* $R^2$ *from the FMB procedure, the OLS adj-*$R^2$ *from GMM1 and the GLS adj-*$R^2$ *from GMM2. The* $\chi^2$ *test statistic is used to measure the degree of portfolio mispricing. The p-value (reported in parentheses) is for the null hypothesis that all portfolios are jointly 'priced', in that the pricing errors are not statistically different from zero. I also report the root mean squared pricing errors (RMSPE) and correlation of the HML factor with the second principal component of five forward-premia-sorted portfolios (*$\rho$*). In Panel A, 12 test asset portfolios are used in the investigation, including the pricing factors themselves. In Panel B, the number of test assets is expanded to 22. Full details on the formation of the test portfolios and pricing factors, as well as the data used in their construction, can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 27].*

| All Countries: Fama-MacBeth Time-Series Regressions | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Resilience to World Disasters** | | | | **Time-varying Surplus-Consumption** | | | | **Share of World Consumption** | | | |
| Portfolio | $\alpha$ | $\beta_{DOL}$ | $\beta_{HML}$ | $R^2$ | $\alpha$ | $\beta_{DOL}$ | $\beta_{HML}$ | $R^2$ | $\alpha$ | $\beta_{DOL}$ | $\beta_{HML}$ | $R^2$ |
| **Forward-Premia Sorted Portfolios** | | | | | | | | | | | | |
| 1 (*Low IR*) | -2.73 | 0.81 | 0.10 | 72.9% | -2.39 | 0.85 | -0.16 | 73.0% | -2.77 | 0.89 | 0.24 | 74.2% |
| | *(0.90)* | *(0.05)* | *(0.07)* | | *(0.87)* | *(0.05)* | *(0.06)* | | *(0.89)* | *(0.05)* | *(0.08)* | |
| 2 | -3.30 | 0.86 | 0.04 | 77.2% | -2.84 | 0.88 | -0.18 | 76.0% | -3.26 | 0.97 | -0.07 | 77.6% |
| | *(0.78)* | *(0.05)* | *(0.10)* | | *(0.77)* | *(0.04)* | *(0.06)* | | *(0.73)* | *(0.04)* | *(0.08)* | |
| 3 | -0.35 | 0.91 | 0.05 | 82.4% | -0.63 | 0.97 | 0.06 | 83.6% | -0.36 | 1.03 | 0.06 | 84.6% |
| | *(0.64)* | *(0.04)* | *(0.06)* | | *(0.63)* | *(0.04)* | *(0.06)* | | *(0.59)* | *(0.04)* | *(0.06)* | |
| 4 | -1.03 | 0.99 | 0.06 | 81.4% | -1.44 | 1.06 | 0.10 | 83.8% | -1.02 | 1.11 | 0.03 | 82.7% |
| | *(0.90)* | *(0.05)* | *(0.06)* | | *(0.80)* | *(0.04)* | *(0.05)* | | *(0.82)* | *(0.05)* | *(0.08)* | |
| 5 (*High IR*) | 2.33 | 1.01 | -0.27 | 64.2% | 1.88 | 0.99 | 0.18 | 62.9% | 2.57 | 1.07 | -0.22 | 61.8% |
| | *(1.18)* | *(0.06)* | *(0.13)* | | *(1.32)* | *(0.07)* | *(0.10)* | | *(1.28)* | *(0.08)* | *(0.15)* | |
| **Risk Factors** | | | | | | | | | | | | |
| *DOL* | 0.00 | 1.00 | 0.00 | 100% | 0.00 | 1.00 | 0.00 | 100% | 0.00 | 1.00 | 0.00 | 100% |
| | *(0.00)* | *(0.00)* | *(0.00)* | | *(0.00)* | *(0.00)* | *(0.00)* | | *(0.00)* | *(0.00)* | *(0.00)* | |
| *HML* | 0.00 | 0.00 | 1.00 | 100% | 0.00 | 0.00 | 1.00 | 100% | 0.00 | 0.00 | 1.00 | 100% |
| | *(0.00)* | *(0.00)* | *(0.00)* | | *(0.00)* | *(0.00)* | *(0.00)* | | *(0.00)* | *(0.00)* | *(0.00)* | |
| **Characteristic Sorted Portfolios** | | | | | | | | | | | | |
| 1 (*Low RISK*) | -0.26 | 0.99 | -0.76 | 79.7% | 0.34 | 0.95 | -0.64 | 85.4% | 0.84 | 0.91 | -0.71 | 77.7% |
| | *(0.83)* | *(0.05)* | *(0.09)* | | *(0.68)* | *(0.04)* | *(0.07)* | | *(0.77)* | *(0.07)* | *(0.10)* | |
| 2 | 0.47 | 1.02 | -0.20 | 81.3% | -0.13 | 1.03 | -0.37 | 87.6% | -0.56 | 1.07 | -0.40 | 82.5% |
| | *(0.76)* | *(0.04)* | *(0.06)* | | *(0.58)* | *(0.03)* | *(0.05)* | | *(0.76)* | *(0.06)* | *(0.10)* | |
| 3 | -0.41 | 0.98 | -0.08 | 76.4% | -0.43 | 1.05 | 0.02 | 86.1% | -0.51 | 1.04 | 0.22 | 82.4% |
| | *(0.91)* | *(0.06)* | *(0.06)* | | *(0.64)* | *(0.04)* | *(0.06)* | | *(0.78)* | *(0.05)* | *(0.05)* | |
| 4 | -0.48 | 0.97 | 0.47 | 87.9% | -0.48 | 1.04 | 0.48 | 85.0% | 0.36 | 1.01 | 0.30 | 84.8% |
| | *(0.63)* | *(0.03)* | *(0.07)* | | *(0.84)* | *(0.05)* | *(0.05)* | | *(0.75)* | *(0.07)* | *(0.06)* | |
| 5 (*High RISK*) | 0.58 | 1.03 | 0.57 | 89.4% | 0.70 | 0.94 | 0.51 | 82.9% | -0.11 | 0.97 | 0.58 | 86.9% |
| | *(0.65)* | *(0.04)* | *(0.07)* | | *(0.84)* | *(0.05)* | *(0.05)* | | *(0.67)* | *(0.05)* | *(0.05)* | |

**Table 6:** ***Time-Series Asset Pricing Tests: All Countries.*** *The table presents the first stage time-series regressions from the Fama-MacBeth (FMB) procedure for the All Countries Sample. The returns to 12 test asset portfolios are regressed on a constant, the DOL factor (the average return across five forward-premia sorted portfolios) and an HML-style factor. The three HML-style factors are constructed to proxy for the theory-driven predictions for currency risk exposure: resilience to world disasters, time-varying surplus-consumption ratio and the share of world consumption. I report the coefficient estimates for the constant ($\alpha$), DOL ($\beta_{DOL}$) and HML ($\beta_{HML}$), along with Newey-West (1987) corrected standard errors. I also report OLS $R^2$ statistics for each of the 12 regressions. The cross-sectional results associated with the estimated coefficients can be found in Panel A of Table 4. Full details on the formation of the test portfolios and pricing factors, as well as the data used in their construction, can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 28].*

| Developed Countries: Fama-MacBeth Time-Series Regressions | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Resilience to World Disasters** | | | | **Time-varying Surplus-Consumption** | | | | **Share of World Consumption** | | | |
| Portfolio | $\alpha$ | $\beta_{DOL}$ | $\beta_{HML}$ | $R^2$ | $\alpha$ | $\beta_{DOL}$ | $\beta_{HML}$ | $R^2$ | $\alpha$ | $\beta_{DOL}$ | $\beta_{HML}$ | $R^2$ |
| **Forward-Premia Sorted Portfolios** | | | | | | | | | | | | |
| 1 (*Low IR*) | -2.58 | 0.95 | -0.12 | 64.2% | -2.06 | 0.92 | -0.12 | 64.9% | -2.04 | 1.04 | 0.66 | 74.4% |
| | *(1.37)* | *(0.08)* | *(0.09)* | | *(1.30)* | *(0.07)* | *(0.09)* | | *(1.07)* | *(0.06)* | *(0.08)* | |
| 2 | -1.68 | 0.96 | 0.31 | 84.2% | -0.90 | 1.00 | -0.25 | 84.4% | -1.66 | 1.03 | 0.11 | 82.0% |
| | *(0.73)* | *(0.04)* | *(0.05)* | | *(0.68)* | *(0.04)* | *(0.07)* | | *(0.74)* | *(0.04)* | *(0.08)* | |
| 3 | -0.85 | 0.96 | 0.19 | 85.6% | -0.84 | 0.99 | 0.03 | 85.7% | -0.88 | 0.99 | 0.00 | 85.7% |
| | *(0.61)* | *(0.04)* | *(0.06)* | | *(0.62)* | *(0.04)* | *(0.06)* | | *(0.62)* | *(0.04)* | *(0.06)* | |
| 4 | 0.43 | 1.04 | -0.10 | 82.9% | -0.74 | 1.02 | 0.17 | 83.3% | -0.45 | 0.98 | -0.13 | 82.3% |
| | *(0.87)* | *(0.04)* | *(0.06)* | | *(0.86)* | *(0.04)* | *(0.05)* | | *(0.90)* | *(0.04)* | *(0.07)* | |
| 5 (*High IR*) | 2.37 | 1.14 | -0.34 | 68.6% | 2.17 | 1.06 | 0.16 | 66.5% | 1.98 | 0.94 | -0.70 | 76.6% |
| | *(1.22)* | *(0.06)* | *(0.13)* | | *(1.16)* | *(0.06)* | *(0.11)* | | *(0.99)* | *(0.05)* | *(0.10)* | |
| **Risk Factors** | | | | | | | | | | | | |
| *DOL* | 0.00 | 1.00 | 0.00 | 100% | 0.00 | 1.00 | 0.00 | 100% | 0.00 | 1.00 | 0.00 | 100% |
| | *(0.00)* | *(0.00)* | *(0.00)* | | *(0.00)* | *(0.00)* | *(0.00)* | | *(0.00)* | *(0.00)* | *(0.00)* | |
| *HML* | 0.00 | 0.00 | 1.00 | 100% | 0.00 | 0.00 | 1.00 | 100% | 0.00 | 0.00 | 1.00 | 100% |
| | *(0.00)* | *(0.00)* | *(0.00)* | | *(0.00)* | *(0.00)* | *(0.00)* | | *(0.00)* | *(0.00)* | *(0.00)* | |
| **Characteristic Sorted Portfolios** | | | | | | | | | | | | |
| 1 (*Low RISK*) | -0.94 | 0.94 | -0.85 | 77.3% | -0.76 | 1.04 | -0.68 | 87.6% | 1.06 | 0.92 | -0.64 | 90.0% |
| | *(0.84)* | *(0.05)* | *(0.09)* | | *(0.95)* | *(0.05)* | *(0.06)* | | *(0.63)* | *(0.02)* | *(0.06)* | |
| 2 | 0.65 | 1.11 | -0.07 | 86.2% | 0.84 | 0.96 | -0.35 | 84.5% | 0.56 | 1.17 | -0.17 | 89.2% |
| | *(0.71)* | *(0.04)* | *(0.08)* | | *(0.88)* | *(0.05)* | *(0.05)* | | *(0.70)* | *(0.03)* | *(0.07)* | |
| 3 | 0.56 | 0.91 | -0.16 | 72.3% | -0.17 | 1.02 | 0.06 | 81.9% | -0.98 | 0.83 | -0.39 | 82.0% |
| | *(0.91)* | *(0.05)* | *(0.07)* | | *(0.78)* | *(0.04)* | *(0.06)* | | *(0.72)* | *(0.04)* | *(0.06)* | |
| 4 | -0.52 | 0.97 | 0.61 | 91.8% | -0.39 | 0.97 | 0.44 | 84.8% | 0.75 | 1.03 | 0.48 | 83.4% |
| | *(0.54)* | *(0.03)* | *(0.05)* | | *(0.77)* | *(0.03)* | *(0.04)* | | *(0.81)* | *(0.04)* | *(0.05)* | |
| 5 (*High RISK*) | 0.24 | 1.08 | 0.47 | 91.4% | 0.47 | 1.02 | 0.53 | 86.8% | -0.26 | 1.06 | 0.72 | 84.2% |
| | *(0.62)* | *(0.03)* | *(0.04)* | | *(0.76)* | *(0.03)* | *(0.05)* | | *(0.80)* | *(0.04)* | *(0.06)* | |

**Table 7:** ***Time-Series Asset Pricing Tests: Developed Countries.*** *The table presents the first stage time-series regressions from the Fama-MacBeth (FMB) procedure for the Developed Countries Sample. The returns to 12 test asset portfolios are regressed on a constant, the DOL factor (the average return across five forward-premia sorted portfolios) and an HML-style factor. The three HML-style factors are constructed to proxy for the theory-driven predictions for currency risk exposure: resilience to world disasters, time-varying surplus-consumption ratio and the share of world consumption. I report the coefficient estimates for the constant ($\alpha$), DOL ($\beta_{DOL}$) and HML ($\beta_{HML}$), along with Newey-West (1987) corrected standard errors. I also report OLS $R^2$ statistics for each of the 12 regressions. The cross-sectional results associated with the estimated coefficients can be found in Panel A of Table 5. Full details on the formation of the test portfolios and pricing factors, as well as the data used in their construction, can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 29].*

**Panel A: Cross-Section Regressions**

| | **Financial Risk** | | **FX Stability** | | **Int. Liquidity** | | **Current Account** | | **Debt Service** | | **Foreign Debt** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ |
| *FMB* | 1.94 | 0.98 | 2.02 | 2.31 | 2.05 | 0.79 | 2.06 | 1.13 | 2.04 | 0.34 | 2.08 | 1.50 |
| *Std. Error* | (1.40) | (1.26) | (1.40) | (0.95) | (1.38) | (0.82) | (1.37) | (1.11) | (1.36) | (0.77) | (1.40) | (0.92) |
| | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ |
| *GMM2* | 0.30 | 0.21 | 0.25 | 0.83 | 0.33 | 0.46 | 0.39 | 0.40 | 0.33 | -0.09 | 0.39 | 0.91 |
| *Std. Error* | (0.27) | (0.29) | (0.26) | (0.37) | (0.26) | (0.39) | (0.29) | (0.32) | (0.26) | (0.47) | (0.28) | (0.38) |

*Cross-sectional regression statistics*

| | *FMB* | *GMM2* | *FMB* | *GMM2* | *FMB* | *GMM2* | *FMB* | *GMM2* | *FMB* | *GMM2* | *FMB* | *GMM2* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $R^2$ | 11.9% | -11.7% | 33.1% | 11.3% | 20.6% | -4.9% | 27.9% | 3.5% | 21.0% | -5.0% | 26.5% | 2.0% |
| *RMSPE* | 1.61% | 1.64% | 1.28% | 1.33% | 1.45% | 1.50% | 1.32% | 1.38% | 1.50% | 1.56% | 1.37% | 1.44% |

**Panel B: Time-Series Regressions (12 Portfolios)**

| | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Forward-Premia Sorted Portfolios** | | | | | | | | | | | | |
| 1 (*Low IR*) | -0.35 | 79.4% | -0.13 | 72.2% | -0.21 | 71.9% | -0.38 | 78.9% | -0.20 | 72.4% | -0.36 | 76.3% |
| | (0.05) | | (0.07) | | (0.08) | | (0.06) | | (0.09) | | (0.07) | |
| 2 | -0.14 | 78.0% | -0.20 | 78.3% | -0.12 | 77.0% | -0.01 | 77.3% | -0.16 | 77.5% | -0.15 | 77.8% |
| | (0.07) | | (0.09) | | (0.10) | | (0.06) | | (0.09) | | (0.09) | |
| 3 | -0.14 | 83.0% | -0.07 | 82.3% | 0.00 | 83.4% | -0.13 | 83.9% | 0.05 | 83.4% | -0.07 | 83.3% |
| | (0.05) | | (0.06) | | (0.07) | | (0.05) | | (0.07) | | (0.05) | |
| 4 | 0.02 | 80.1% | 0.02 | 80.9% | 0.06 | 82.4% | 0.04 | 81.9% | 0.05 | 82.9% | 0.17 | 82.8% |
| | (0.07) | | (0.08) | | (0.08) | | (0.06) | | (0.08) | | (0.08) | |
| 5 (*High IR*) | 0.43 | 70.9% | 0.27 | 63.4% | 0.16 | 61.5% | 0.42 | 66.4% | 0.12 | 59.9% | 0.31 | 62.4% |
| | (0.07) | | (0.10) | | (0.14) | | (0.09) | | (0.13) | | (0.12) | |
| **Characteristic Sorted Portfolios** | | | | | | | | | | | | |
| 1 (*Low RISK*) | -0.62 | 92.9% | -0.48 | 86.2% | -0.61 | 87.5% | -0.61 | 90.4% | -0.46 | 83.1% | -0.52 | 91.1% |
| | (0.05) | | (0.07) | | (0.08) | | (0.04) | | (0.07) | | (0.07) | |
| 2 | -0.29 | 89.2% | -0.51 | 87.1% | -0.38 | 85.6% | -0.36 | 90.3% | -0.49 | 84.8% | -0.43 | 81.3% |
| | (0.04) | | (0.08) | | (0.07) | | (0.04) | | (0.07) | | (0.09) | |
| 3 | -0.17 | 82.4% | -0.01 | 79.2% | -0.02 | 85.3% | -0.04 | 80.7% | -0.09 | 84.7% | -0.09 | 80.1% |
| | (0.05) | | (0.07) | | (0.06) | | (0.05) | | (0.07) | | (0.06) | |
| 4 | 0.28 | 75.5% | 0.32 | 82.9% | 0.45 | 83.5% | 0.28 | 80.5% | 0.39 | 86.4% | 0.42 | 82.2% |
| | (0.09) | | (0.09) | | (0.08) | | (0.05) | | (0.08) | | (0.07) | |
| 5 (*High RISK*) | 0.80 | 85.7% | 0.68 | 84.3% | 0.46 | 78.8% | 0.74 | 81.1% | 0.65 | 75.5% | 0.63 | 85.7% |
| | (0.09) | | (0.11) | | (0.08) | | (0.05) | | (0.09) | | (0.07) | |

**Table 8:** ***Asset Pricing Tests: Financial Risks.*** *The table presents cross-sectional and time-series asset pricing results for factors constructed to represent financial risk characteristics. The factors are tested using both the Fama-MacBeth procedure as well as a Generalized Method of Moments estimation. In GMM2, the weighting matrix is an optimally constructed matrix to maximize the efficiency of the estimation. The test assets are 12 currency portfolios, including five forward-premia-sorted portfolios, five characteristic-sorted portfolios and the two pricing factors. The pricing factors are DOL risk (the average return across five forward-premia-sorted portfolios) and the HML-style factor for each characteristic. The HML factor is first constructed by sorting currencies into one of five portfolios, on the basis of the implied source of currency risk exposure. Once the five portfolios are finalized, the factor is constructed as* $[(P5+P4)-(P1+P2)]/2$. *Cross-sectional regression statistics are reported in Panel A. The factor prices of risk* $\lambda$ *and Shanken (1992) corrected standard errors are estimated using the FMB procedure. I also present the estimated b's from the Stochastic Discount Factor, estimated using GMM2. Cross-sectional goodness-of-fit statistics include the OLS* $R^2$ *from FMB and the GLS adj-*$R^2$ *from GMM2. In Panel B, I report the first-stage time-series regressions from the FMB procedure, including the OLS* $R^2$ *statistic. Standard errors are corrected according to Newey and West (1987). Full details on the formation of the test portfolios and pricing factors, as well as the data used in their construction, can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 30].*

| | Economic Risk | | GDP per Capita | | GDP Growth Rate | | Inflation Rate | | Budget Balance | | Current Account | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Cross-Section Regressions** | | | | | | | | | | | | |
| | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ |
| *FMB* | 2.05 | 2.46 | 2.09 | 2.28 | 2.06 | 0.95 | 2.05 | 2.13 | 2.09 | 2.02 | 2.07 | 1.93 |
| *Std. Error* | (1.42) | (1.07) | (1.36) | (1.03) | (1.38) | (0.95) | (1.40) | (1.07) | (1.39) | (0.95) | (1.37) | (1.01) |
| | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ |
| *GMM2* | 0.17 | 0.44 | 0.88 | 1.38 | 0.27 | 0.41 | 0.09 | 0.42 | 0.56 | 1.14 | 0.38 | 0.87 |
| *Std. Error* | (0.12) | (0.30) | (0.28) | (0.35) | (0.24) | (0.34) | (0.28) | (0.35) | (0.27) | (0.33) | (0.27) | (0.35) |
| *Cross-sectional regression statistics* | | | | | | | | | | | | |
| | $FMB$ | $GMM2$ | $FMB$ | $GMM2$ | $FMB$ | $GMM2$ | $FMB$ | $GMM2$ | $FMB$ | $GMM2$ | $FMB$ | $GMM2$ |
| $R^2$ | 56.6% | 38.5% | 51.5% | 29.2% | 21.2% | -6.7% | 43.1% | 24.9% | 33.8% | 11.4% | 36.7% | 10.7% |
| *RMSPE* | 1.06% | 1.14% | 1.16% | 1.27% | 1.39% | 1.47% | 1.19% | 1.24% | 1.26% | 1.32% | 1.25% | 1.35% |
| **Panel B: Time-Series Regressions (12 Portfolios)** | | | | | | | | | | | | |
| | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ |
| **Forward-Premia Sorted Portfolios** | | | | | | | | | | | | |
| 1 (*Low IR*) | -0.46 | 81.0% | -0.37 | 76.4% | -0.19 | 72.9% | -0.30 | 75.6% | -0.12 | 72.0% | -0.30 | 75.1% |
| | (0.06) | | (0.05) | | (0.07) | | (0.06) | | (0.09) | | (0.07) | |
| 2 | -0.12 | 76.8% | -0.26 | 78.9% | -0.09 | 76.7% | -0.25 | 79.3% | -0.18 | 78.0% | -0.17 | 78.1% |
| | (0.09) | | (0.04) | | (0.05) | | (0.08) | | (0.09) | | (0.09) | |
| 3 | -0.24 | 84.5% | -0.07 | 83.1% | -0.11 | 83.4% | -0.19 | 83.5% | -0.08 | 83.1% | -0.09 | 83.6% |
| | (0.05) | | (0.05) | | (0.06) | | (0.06) | | (0.06) | | (0.05) | |
| 4 | -0.04 | 80.2% | 0.02 | 82.2% | -0.03 | 81.9% | -0.05 | 80.2% | 0.02 | 82.0% | 0.03 | 81.9% |
| | (0.08) | | (0.06) | | (0.06) | | (0.09) | | (0.07) | | (0.07) | |
| 5 (*High IR*) | 0.66 | 76.0% | 0.60 | 70.5% | 0.33 | 63.8% | 0.64 | 74.7% | 0.29 | 63.0% | 0.48 | 66.9% |
| | (0.09) | | (0.08) | | (0.10) | | (0.07) | | (0.11) | | (0.08) | |
| **Characteristic Sorted Portfolios** | | | | | | | | | | | | |
| 1 (*Low RISK*) | -0.52 | 93.1% | -0.47 | 89.0% | -0.51 | 86.7% | -0.65 | 86.3% | -0.58 | 90.3% | -0.50 | 88.4% |
| | (0.03) | | (0.04) | | (0.05) | | (0.07) | | (0.07) | | (0.07) | |
| 2 | -0.40 | 89.3% | -0.40 | 89.2% | -0.41 | 85.4% | -0.31 | 86.5% | -0.36 | 86.0% | -0.46 | 87.4% |
| | (0.03) | | (0.04) | | (0.05) | | (0.06) | | (0.06) | | (0.08) | |
| 3 | -0.17 | 83.0% | -0.24 | 83.5% | -0.18 | 79.3% | -0.08 | 83.8% | -0.11 | 81.5% | -0.08 | 83.4% |
| | (0.04) | | (0.05) | | (0.06) | | (0.07) | | (0.06) | | (0.06) | |
| 4 | 0.14 | 79.9% | 0.40 | 79.4% | 0.35 | 85.3% | 0.20 | 77.8% | 0.39 | 85.2% | 0.34 | 82.3% |
| | (0.09) | | (0.08) | | (0.05) | | (0.12) | | (0.05) | | (0.05) | |
| 5 (*High RISK*) | 0.95 | 86.5% | 0.72 | 69.8% | 0.74 | 84.0% | 0.84 | 82.0% | 0.66 | 82.7% | 0.71 | 77.9% |
| | (0.10) | | (0.08) | | (0.06) | | (0.14) | | (0.06) | | (0.07) | |

**Table 9:** ***Asset Pricing Tests: Economic Risks.*** *The table presents cross-sectional and time-series asset pricing results for factors constructed to represent economic risk characteristics. The factors are tested using both the Fama-MacBeth procedure as well as a Generalized Method of Moments estimation. In GMM2, the weighting matrix is an optimally constructed matrix to maximize the efficiency of the estimation. The test assets are 12 currency portfolios, including five forward-premia-sorted portfolios, five characteristic-sorted portfolios and the two pricing factors. The pricing factors are DOL risk (the average return across five forward-premia-sorted portfolios) and the HML-style factor for each characteristic. The HML factor is first constructed by sorting currencies into one of five portfolios, on the basis of the implied source of currency risk exposure. Once the five portfolios are finalized, the factor is constructed as* $[(P5 + P4) - (P1 + P2)]/2$. *Cross-sectional regression statistics are reported in Panel A. The factor prices of risk* $\lambda$ *and Shanken (1992) corrected standard errors are estimated using the FMB procedure. I also present the estimated b's from the Stochastic Discount Factor, estimated using GMM2. Cross-sectional goodness-of-fit statistics include the OLS* $R^2$ *from FMB and the GLS adj-*$R^2$ *from GMM2. In Panel B, I report the first-stage time-series regressions from the FMB procedure, including the OLS* $R^2$ *statistic. Standard errors are corrected according to Newey and West (1987). Full details on the formation of the test portfolios and pricing factors, as well as the data used in their construction, can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 31].*

| | Political Risk | | Govnt. Stability | | Socio. Conditions | | Investment Profile | | Internal Conflict | | External Conflict | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Cross-Section Regressions** | | | | | | | | | | | | |
| | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ |
| *FMB* | 2.05 | -0.34 | 2.05 | -0.35 | 2.13 | 2.44 | 2.08 | 2.11 | 2.04 | 0.84 | 2.04 | 1.51 |
| *Std. Error* | (1.37) | (1.20) | (1.40) | (1.38) | (1.39) | (0.97) | (1.37) | (0.94) | (1.39) | (0.88) | (1.38) | (0.89) |
| | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ |
| *GMM2* | 0.24 | -0.00 | 0.42 | -0.26 | 0.41 | 1.28 | 0.64 | 1.32 | 0.23 | 0.52 | 0.04 | 0.94 |
| *Std. Error* | (0.30) | (0.29) | (0.26) | (0.39) | (0.27) | (0.35) | (0.29) | (0.39) | (0.25) | (0.37) | (0.29) | (0.40) |
| *Cross-sectional regression statistics* | | | | | | | | | | | | |
| | *FMB* | *GMM2* | *FMB* | *GMM2* | *FMB* | *GMM2* | *FMB* | *GMM2* | *FMB* | *GMM2* | *FMB* | *GMM2* |
| $R^2$ | 27.9% | 7.6% | 20.4% | -3.1% | 42.1% | 22.7% | 44.1% | 17.9% | 8.4% | -17.6% | 39.3% | 4.6% |
| *RMSPE* | 1.50% | 1.54% | 1.50% | 1.54% | 1.25% | 1.31% | 1.17% | 1.29% | 1.48% | 1.52% | 1.31% | 1.49% |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel B: Time-Series Regressions (12 Portfolios)** | | | | | | | | | | | | |
| | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ | $\beta_{HML}$ | $R^2$ |
| **Forward-Premia Sorted Portfolios** | | | | | | | | | | | | |
| 1 (*Low IR*) | -0.27 | 74.6% | -0.13 | 72.2% | -0.25 | 73.6% | -0.26 | 73.7% | 0.02 | 72.1% | -0.22 | 73.3% |
| | (0.05) | | (0.08) | | (0.07) | | (0.07) | | (0.09) | | (0.09) | |
| 2 | -0.14 | 77.3% | 0.18 | 78.4% | -0.17 | 78.0% | -0.16 | 77.6% | 0.04 | 77.5% | -0.36 | 81.0% |
| | (0.08) | | (0.11) | | (0.09) | | (0.12) | | (0.11) | | (0.09) | |
| 3 | -0.25 | 85.0% | -0.06 | 83.0% | -0.09 | 83.2% | -0.04 | 83.3% | 0.10 | 83.6% | -0.12 | 83.7% |
| | (0.05) | | (0.05) | | (0.05) | | (0.05) | | (0.06) | | (0.06) | |
| 4 | -0.10 | 80.9% | -0.16 | 82.6% | 0.06 | 82.2% | -0.09 | 82.0% | -0.05 | 81.9% | 0.06 | 81.4% |
| | (0.08) | | (0.07) | | (0.07) | | (0.07) | | (0.08) | | (0.08) | |
| 5 (*High IR*) | 0.52 | 72.1% | 0.08 | 60.5% | 0.40 | 64.8% | 0.48 | 66.1% | -0.15 | 60.3% | 0.64 | 68.6% |
| | (0.07) | | (0.12) | | (0.10) | | (0.12) | | (0.14) | | (0.11) | |
| **Characteristic Sorted Portfolios** | | | | | | | | | | | | |
| 1 (*Low RISK*) | -0.46 | 94.0% | -0.49 | 85.5% | -0.66 | 89.1% | -0.49 | 89.7% | -0.62 | 87.2% | -0.57 | 89.8% |
| | (0.02) | | (0.05) | | (0.07) | | (0.04) | | (0.07) | | (0.09) | |
| 2 | -0.42 | 91.0% | -0.44 | 86.0% | -0.28 | 83.9% | -0.43 | 89.0% | -0.40 | 87.4% | -0.37 | 90.9% |
| | (0.03) | | (0.04) | | (0.06) | | (0.04) | | (0.06) | | (0.07) | |
| 3 | -0.23 | 85.0% | -0.14 | 86.5% | -0.10 | 84.8% | -0.16 | 86.3% | 0.04 | 83.8% | -0.13 | 79.7% |
| | (0.05) | | (0.07) | | (0.05) | | (0.05) | | (0.05) | | (0.07) | |
| 4 | 0.08 | 76.0% | 0.53 | 80.6% | 0.40 | 85.7% | 0.39 | 80.0% | 0.37 | 82.2% | 0.65 | 82.7% |
| | (0.09) | | (0.11) | | (0.06) | | (0.10) | | (0.10) | | (0.08) | |
| 5 (*High RISK*) | 1.03 | 84.8% | 0.54 | 76.9% | 0.65 | 82.1% | 0.69 | 73.2% | 0.61 | 84.9% | 0.42 | 82.2% |
| | (0.10) | | (0.10) | | (0.06) | | (0.11) | | (0.09) | | (0.08) | |

**Table 10:** ***Asset Pricing Tests: Political Risks.*** *The table presents cross-sectional and time-series asset pricing results for factors constructed to represent political risk characteristics. The factors are tested using both the Fama-MacBeth procedure as well as a Generalized Method of Moments estimation. In GMM2, the weighting matrix is an optimally constructed matrix to maximize the efficiency of the estimation. The test assets are 12 currency portfolios, including five forward-premia-sorted portfolios, five characteristic-sorted portfolios and the two pricing factors. The pricing factors are DOL risk (the average return across five forward-premia-sorted portfolios) and the HML-style factor for each characteristic. The HML factor is first constructed by sorting currencies into one of five portfolios, on the basis of the implied source of currency risk exposure. Once the five portfolios are finalized, the factor is constructed as* $[(P5 + P4) - (P1 + P2)]/2$. *Cross-sectional regression statistics are reported in Panel A. The factor prices of risk* $\lambda$ *and Shanken (1992) corrected standard errors are estimated using the FMB procedure. I also present the estimated b's from the Stochastic Discount Factor, estimated using GMM2. Cross-sectional goodness-of-fit statistics include the OLS* $R^2$ *from FMB and the GLS adj-*$R^2$ *from GMM2. In Panel B, I report the first-stage time-series regressions from the FMB procedure, including the OLS* $R^2$ *statistic. Standard errors are corrected according to Newey and West (1987). Full details on the formation of the test portfolios and pricing factors, as well as the data used in their construction, can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 31].*

| Factor Correlations | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | S-C | BB | IP | CA | PC | SC | CV | DO |
| *Surplus Consumption (S-C)* | | | | | | | | |
| *Budget Balance (BB)* | 0.03 | | | | | | | |
| *Investment Profile (IP)* | 0.15 | 0.19 | | | | | | |
| *Current Account (CA)* | 0.22 | 0.44 | 0.20 | | | | | |
| *Per Capita GDP (PC)* | 0.14 | 0.49 | 0.50 | 0.44 | | | | |
| *Socioeconomic Conditions (SC)* | 0.02 | 0.27 | 0.31 | 0.20 | 0.35 | | | |
| *Currency Volatility (CV)* | 0.01 | 0.17 | 0.02 | 0.34 | 0.06 | 0.23 | | |
| *Dollar Risk (DO)* | -0.04 | -0.09 | -0.29 | -0.01 | -0.31 | -0.08 | 0.13 | |

**Table 11:** ***Correlations between Characteristic Pricing Factors.*** *The table presents the correlations between theory-based and alternative characteristic pricing factors. Full details on the formation of the pricing factors, as well as the data used in their construction, can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 32].*

**Panel A: Multi-Factor Regression with 58 Test Asset Portfolios**

| | $\lambda_{DOL}$ | $\lambda_{S-C}$ | $\lambda_{BB}$ | $\lambda_{IP}$ | $\lambda_{CA}$ | $\lambda_{PC}$ | $\lambda_{SC}$ | $\lambda_{CV}$ | $\lambda_{Slope}$ | *Statistics* | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *FMB* | 2.39 | 2.91 | 1.07 | 1.49 | 1.41 | 1.04 | 1.77 | 1.50 | 5.26 | $R^2$ (OLS) | 67.4% |
| *Std. Error* | (1.44) | (1.08) | (0.90) | (0.97) | (0.97) | (0.92) | (0.90) | (0.92) | (1.73) | $R^2$ (GLS) | 46.9% |
| | $b_{DOL}$ | $b_{S-C}$ | $b_{BB}$ | $b_{IP}$ | $b_{CA}$ | $b_{PC}$ | $b_{SC}$ | $b_{CV}$ | $b_{Slope}$ | *RMSPE* | 0.73% |
| *GMM2* | 0.49 | 1.02 | 0.33 | 0.61 | -0.17 | -0.34 | 0.36 | 0.44 | 0.54 | $\chi^2$ | 71.9 |
| *Std. Error* | (0.30) | (0.33) | (0.48) | (0.48) | (0.46) | (0.54) | (0.44) | (0.43) | (0.31) | *p-value* | 0.02 |

**Panel B: Individual Cross-Sectional Regressions with 58 Test Asset Portfolios**

| | **Surp.-Consump** | | **Invest. Profile** | | **Current Acc.** | | **Slope Risk** | |
|---|---|---|---|---|---|---|---|---|
| | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ | $\lambda_{DOL}$ | $\lambda_{HML}$ |
| *FMB* | 2.41 | 3.96 | 2.27 | 3.40 | 2.55 | 3.80 | 2.41 | 6.40 |
| *Std. Error* | (1.47) | (1.18) | (1.46) | (1.21) | (2.55) | (1.27) | (1.46) | (1.93) |
| | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ | $b_{DOL}$ | $b_{HML}$ |
| *GMM2* | 0.44 | 1.53 | 0.87 | 2.12 | 0.46 | 1.66 | 0.37 | 0.90 |
| *Std. Error* | (0.26) | (0.33) | (0.29) | (0.42) | (0.27) | (0.32) | (0.26) | (0.25) |
| | *Cross-sectional regression statistics* | | | | | | | |
| $R^2$ (OLS) | 24.7% | | 32.8% | | 35.8% | | 50.5% | |
| $R^2$ (GLS) | 9.7% | | 1.1% | | -1.7% | | 40.3% | |
| *RMSPE* | 1.11% | | 1.05% | | 1.02% | | 0.90% | |
| $\chi^2$ | 71.8 | | 71.0% | | 73.5 | | 71.7 | |
| *p-value* | 0.08 | | 0.09 | | 0.06 | | 0.08 | |

**Panel C: Multi-Factor Regressions with 58 Test Asset Portfolios**

| | $\lambda_{DOL}$ | $\lambda_{S-C}$ | $\lambda_{IP}$ | $\lambda_{DOL}$ | $\lambda_{S-C}$ | $\lambda_{CA}$ | $\lambda_{DOL}$ | $\lambda_{S-C}$ | $\lambda_{IP}$ | $\lambda_{CA}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| *FMB* | 2.28 | 3.32 | 2.88 | 2.52 | 3.10 | 3.33 | 2.39 | 2.99 | 2.24 | 2.66 |
| *Std. Error* | (1.46) | (1.12) | (1.18) | (1.47) | (1.09) | (1.26) | (1.46) | (1.09) | (1.04) | (1.18) |
| | $b_{DOL}$ | $b_{S-C}$ | $b_{IP}$ | $b_{DOL}$ | $b_{S-C}$ | $b_{CA}$ | $b_{DOL}$ | $b_{S-C}$ | $b_{IP}$ | $b_{CA}$ |
| *GMM2* | 0.81 | 1.10 | 1.70 | 0.52 | 1.08 | 1.30 | 0.74 | 0.96 | 1.21 | 0.83 |
| *Std. Error* | (0.30) | (0.35) | (0.44) | (0.27) | (0.37) | (0.34) | (0.30) | (0.36) | (0.44) | (0.39) |
| | *Cross-sectional regression statistics* | | | | | | | | | |
| $R^2$ (OLS) | 51.7% | | | 48.5% | | | 58.1% | | | |
| $R^2$ (GLS) | 27.2% | | | 19.2% | | | 30.2% | | | |
| *RMSPE* | 0.89% | | | 0.92% | | | 0.83% | | | |
| $\chi^2$ | 70.8 | | | 72.4 | | | 71.6 | | | |
| *p-value* | 0.07 | | | 0.06 | | | 0.05 | | | |

**Table 12:** ***Asset Pricing with Alternative Characteristic Factors.*** *The table presents cross-sectional asset pricing tests using the Fama-MacBeth (FMB) procedure and a Generalized Method of Moments (GMM) estimation. In GMM2, the weighting matrix is an optimally constructed matrix to maximize the efficiency of the estimation. In Panel A, I investigate the pricing performance of theory-driven and alternative characteristic factors when pricing 58 test asset portfolios. I report factor prices of risk $\lambda$ and Shanken (1992) corrected standard errors to test if the factors are priced. The b's from the Stochastic Discount Factor (SDF) with associated standard errors are estimated using the GMM2 procedure. I also report cross-sectional goodness-of-fit statistics, including the OLS $R^2$ and root mean squared pricing error (RMSPE) from the FMB procedure and the GLS adj-$R^2$ and $\chi^2$ test statistic from the GMM2 estimation. A p-value greater than 0.05 from the $\chi^2$ test, implies that the null hypothesis that all pricing errors are jointly equal to zero, cannot be rejected. In Panels B, I report cross-sectional asset pricing results for individual characteristic factors when combined with the DOL factor (the average return across five forward-premia-sorted portfolios). In Panel C, I report cross-sectional asset pricing results for models including the best performing characteristic factors, the surplus-consumption factor, as well as DOL risk. Full details on the formation of the test portfolios and pricing factors, as well as the data used in their construction, can be found in Section 3. Data on forward and spot exchange rates are from Barclays and Reuters, available on DataStream. The sample is from 1983 to 2011.* *[Go to page 32].*