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Conditional risk premia in currency markets and other asset classes ☆

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ABSTRACT

The downside risk capital asset pricing model (DR-CAPM) can price the cross section of currency returns. The market-beta differential between high and low interest rate currencies is higher conditional on bad market returns, when the market price of risk is also high, than it is conditional on good market returns. Correctly accounting for this variation is crucial for the empirical performance of the model. The DR-CAPM can jointly rationalize the cross section of equity, equity index options, commodity, sovereign bond and currency returns, thus offering a unified risk view of these asset classes. In contrast, popular models that have been developed for a specific asset class fail to jointly price other asset classes.

1. Introduction

Foreign exchange is a potentially risky investment, and the debate over whether currency returns can be explained by their association with risk factors remains ongoing. We find that the cross section of currency returns can be explained by a risk model in which investors are concerned about downside risk. High-yield currencies earn higher excess returns than low-yield currencies because their co-movement with aggregate market returns is stronger conditional on bad market returns than it is conditional on good market returns. We find that this feature of the data is characteristic not only of currencies but also of equities, commodities, sovereign bonds, and other test assets, thus providing a unified risk view of these markets.

The carry trade in foreign exchange consists of investing in high-yield currencies while funding the trade in

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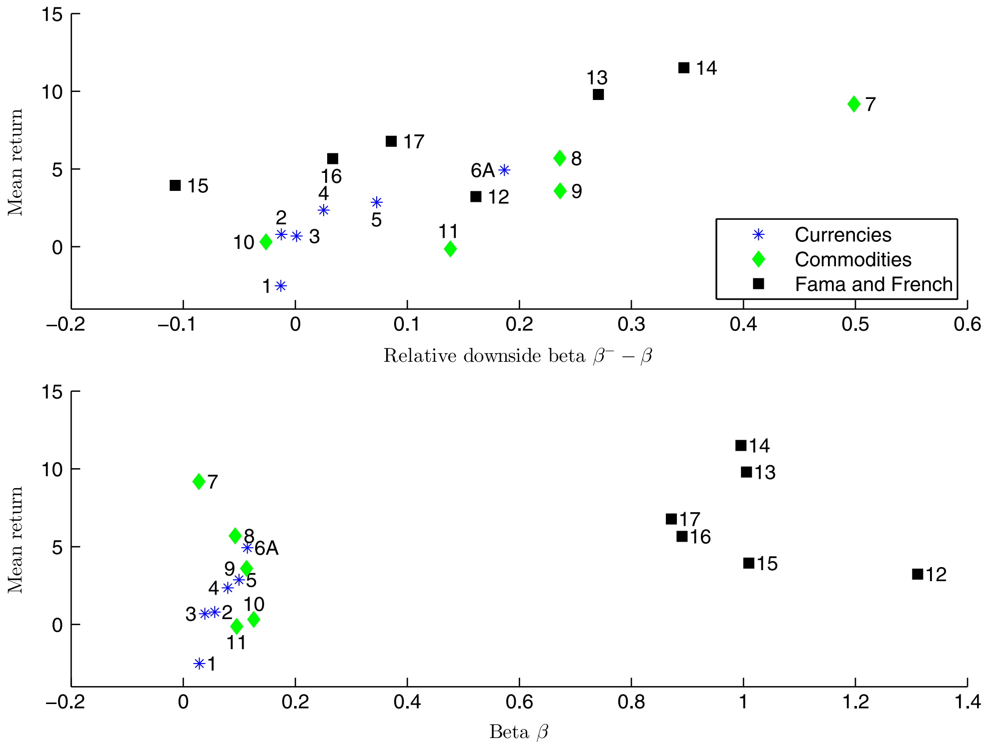

Fig. 1. Risk–return relations.
Depicted are risk–return relations for six currency portfolios monthly re-sampled based on the interest rate differential with the US, six Fama and French equity portfolios sorted on size and book-to-market, and five commodity futures portfolios monthly re-sampled based on basis. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. The top panel plots the realized mean excess return versus the relative downside betas ($\beta^- - \beta$). The bottom panel plots the realized mean excess return versus the capital asset pricing model betas (β). The sample period is January 1974 to March 2010 for a total of 435 observations for the currency and equity portfolios and January 1974 to December 2008 for a total of 420 observations for the commodity portfolios.

low-yield currencies. This trading strategy has historically yielded positive returns because returns on high-yield currencies are higher than returns on low-yield currencies. A number of explanations for this cross-sectional dispersion have been advanced in the literature, varying from risk-based to behavioral.

We suggest a risk-based explanation by showing that the downside risk capital asset pricing model (DR-CAPM) prices the cross section of currency returns. We follow Ang, Chen, and Xing (2006), who study equity markets, by allowing both the market price of risk and the beta of currencies with the market to change conditional on the aggregate market return. Intuitively, the model captures the changes in correlation between the carry trade and the aggregate market returns. The carry trade is more correlated with the market during market downturns than it is during upturns.

Correctly capturing the variations in betas and prices of risk is crucial to the empirical performance of the DR-CAPM. It also clarifies why the unconditional CAPM does not explain the cross section of currency returns. While high-yield currencies have higher betas than lower yield currencies, the difference in betas is too small to account for the observed spread in currency returns.

We extend our results by testing the performance of the DR-CAPM jointly on currencies, various equity portfolios, equity index options, commodities, and sovereign bonds. The variations in betas and prices of risk in the DR-CAPM can jointly capture the cross-sectional returns of all of these asset classes. This contrasts with the inability of a number of asset class-specific models to price asset classes other than the one for which they have been built.

The economic intuition behind our results is summarized in Fig. 1. Across different asset classes such as currencies, commodities, and equities, assets that have higher exposure to downside risk — that is, assets that have a higher downside beta (β^-) — earn higher excess returns even when controlling for their CAPM beta (β).[1] The top panel of Fig. 1 highlights this pattern in the data by plotting realized average excess returns versus the corresponding asset loading on downside risk ($\beta^- - \beta$). The positive relation between expected returns and downside risk is the crucial pattern behind the more formal econometric analysis of this paper. In contrast, the bottom panel of Fig. 1 shows why the CAPM cannot price the returns of these asset classes. Within each asset class there is little dispersion in betas but a larger dispersion in realized returns. Across asset classes the CAPM captures, at best, the average return of each asset class, but no strong systematic relation appears.

[1] See Sections 2 and 3 for the precise definition and estimation procedure of β and β^-.

We compare the DR-CAPM with models based on principal component analysis (PCA) both within and across asset classes. Within each asset class the DR-CAPM captures the cross-sectional dispersion in returns summarized by the most important principal components. Across asset classes the DR-CAPM continues to capture expected returns with only two fundamental factors, while a PCA-based model requires as many as eight factors to generate similar explanatory power.

This paper contributes to two strands of literature: the international finance literature on exchange rates and currency returns and the asset pricing literature on the joint cross section of returns of multiple asset classes.

Among a vast international finance literature, Lustig and Verdelhan (2007) provide an explanation for the cross section of currency returns based on the durable consumption CAPM (DC-CAPM). Burnside (2011b) and Lustig and Verdelhan (2011) discuss the association of currency returns with consumption growth. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Burnside, Eichenbaum, and Rebelo (2011, 2009), and Burnside, Han, Hirshleifer, and Wang (2011) focus on explanations of the carry trade such as investor overconfidence and peso problems. Lustig, Roussanov, and Verdelhan (2011) (LRV) provide a model that employs the principal component analysis of currency returns. They show that currencies that load more heavily on the first two principal components, approximated by the returns on a dollar and carry trade portfolio, respectively, earn higher excess returns on average. Menkhoff, Sarno, Schmeling, and Schrimpf (2012) link the carry trade factor to exchange rate volatility.

Our contribution to this literature is to provide an explanation of currency returns based on the conditional contemporaneous association of currency returns with a traditional risk factor, the market return. We reconcile our findings with the more statistical factors used in the literature and show that currencies are affected by the same aggregate risk that drives expected returns in other assets classes such as equities and commodities.

A nascent literature is exploring the joint cross section of returns in multiple asset classes. Cochrane (2011) emphasizes this research agenda, which aims to reconcile the discount factors in different asset classes. In his 2011 American Finance Association presidential address (see Cochrane, 2011) he ponders: “What is the factor structure of time-varying expected returns? Expected returns vary over time. How correlated is such variation across assets and asset classes? How can we best express that correlation as factor structure?… This empirical project has just begun,… but these are the vital questions.”

In recent and ongoing research Asness, Moskowitz, and Pedersen (2013), Frazzini and Pedersen (2014), and Koijen, Moskowitz, Pedersen, and Vrugt (2013) find that a number of cross-sectional phenomena such as value, carry, momentum, and the slope of the unconditional CAPM-based security market line that were previously shown only for specific asset classes are pervasive across multiple asset classes. We contribute to this literature by showing that the DR-CAPM can jointly reconcile the cross-sectional dispersion in returns across multiple asset classes. We also explore the factor structure by comparing the model with several PCA-based models. We find that PCA-based models tailored to a specific asset class are unable to price other asset classes and that a PCA model based on the joint cross section of multiple asset classes overestimates the number of risk factors. We view our results as a step in the research agenda emphasized by Cochrane (2011).

We stress that the purpose of this paper is not to suggest that the DR-CAPM is the true model of all asset prices nor to discourage the use of PCA to summarize patterns in asset returns. The purpose of this paper is to show that the cross-sectional variation in returns across asset classes can be captured by the association of returns, both unconditionally and conditionally, with a traditional risk factor, the market return. For this purpose and for completeness, we report in Section 6.5 a number of assets that the DR-CAPM does not price well.

In a separate online Appendix we provide a number of details, robustness checks, and extensions of our results that are omitted in the main body of the paper, including a comparison of the DR-CAPM with PCA and co-skewness models.

2. Carry trade, cross-sectional and market returns

We follow Ang, Chen, and Xing (2006) in allowing a differentiation in unconditional and downside risk. This captures the idea that assets that have a higher beta with market returns conditional on low realization of the market return are particularly risky. The economic intuition underlying downside risk is simple: Agents require a premium not only for securities the more their returns covary with the market return, but also, and even more so, when securities covary more with market returns conditional on low market returns. Markowitz (1959) was among the first to recognize the importance of downside risk, formalized in his “semi-variance”, in addition to his more canonical expected return variance framework.[2] While Ang, Chen, and Xing (2006) motivate the above insight using the disappointment aversion model of Gul (1991) further extended by Routledge and Zin (2010), a variety of models are potentially consistent with our findings.[3]

The main insight of this paper is that downside risk is a prevalent feature in many asset classes. We show that expected returns in currency, equity, commodity, sovereign bond and option markets can be explained by a simple beta that measures the downside risk of assets in these asset classes. To capture the relative importance of downside risk, we propose that expected returns follow

$$E[r_i] = \beta_i \lambda + (\beta_i^- - \beta_i)\lambda^-, \quad i = 1, \ldots, N,$$
$$\beta_i = \frac{cov(r_i, r_m)}{var(r_m)},$$

[2] Markowitz (1959, Chapter 9) notes that “variance is superior with respect to (computational) cost, (analytical) convenience, and familiarity. (However), analyses based on semi-variance tend to produce better portfolios than those based on variance”.

[3] A variety of other asymmetrical CAPM models have been derived, for example Leland (1999) and Harvey (2000). Adrian, Etula, and Muir (2014) test a model of financial constraints and leverage in which the discount factor loads on negative outcomes for broker-dealer firms.

$$\beta_i^- = \frac{cov(r_i, r_m | r_m < \delta)}{var(r_m | r_m < \delta)}, \tag{1}$$

where r_i is the log excess return of asset i over the risk-free rate, r_m is the log market excess return, β_i and β_i^- are the unconditional and downside beta defined by an exogenous threshold (δ) for the market return, and λ and λ^- are the unconditional and downside prices of risk, respectively. This empirical framework is flexible in allowing variations both in the quantity and the price of risk while maintaining a parsimonious parametrization with a single threshold δ.

The model reduces to the CAPM in the absence of differential pricing of downside risk from unconditional market risk, $\lambda^- = 0$, or if the downside beta equals the CAPM beta, $\beta_i^- = \beta_i$. As in the case of the CAPM, the model also restricts the unconditional price of risk to equal the expected market excess return:

$$\mathrm{E}[r_m] = \lambda, \tag{2}$$

because both the unconditional and downside beta of the market with itself are equal to one.

To clarify the terminology used in this paper, we employ the concept of conditionality in the context of contemporaneous realizations of states of the world: market return above or below a threshold. A part of the asset pricing literature has instead applied similar terminology in the context of time variation of expected returns and return predictability tests.

We stress that, while we do not allow for time variation in the betas or the prices of risk, our empirical methodology is consistent with some predictability in expected returns. Since we test our model on sorted portfolios that capture a characteristic associated with expected returns, for example, the interest rate differential, we allow for predictability generated by variation over time in this characteristic. Cochrane (2005) notes the similarity between testing the model on sorted portfolios and testing the model on unsorted assets while allowing for time variation in instruments that proxy for managed portfolios. Our procedure, however, does not allow variation in expected returns through time for a fixed characteristic.

For example, we capture the fact that the expected return for a specific currency pair varies through time as the corresponding interest rate differential varies, but we do not allow for the expected return of a specific currency pair to vary through time given a constant interest rate differential. Lustig, Roussanov, and Verdelhan (2011) similarly allow predictability only through variation in the interest rate differential.[4]

Finally, our model specification is similar to the one tested by Ang, Chen, and Xing (2006) on equity portfolios. While the present specification has the convenience of both nesting the CAPM and reducing the number of estimated coefficients in the cross-sectional regression to the price of downside risk λ^-, we report in the online Appendix the estimates for the specification in Ang, Chen, and Xing (2006) for our benchmark test assets.

2.1. Data

Details of the data are included in the online Appendix and a replicating dataset is available on the journal website. The data are monthly, from January 1974 to March 2010, and cover 53 currencies. We follow Lustig and Verdelhan (2007) in defining a cross section of currency returns based on their interest rate. We sort currencies into six portfolios, in ascending order of their respective interest rates.

Since the data-set includes currencies for which the corresponding country has undergone periods of extremely high inflation and consequently high nominal interest rates, we split the sixth portfolio into two baskets: 6A and 6B. Portfolio 6B has currencies that belong to Portfolio 6 and that have annualized inflation at least 10% higher than US inflation in the same month.[5]

We also use an alternative sorting that includes only developed countries' currencies.[6] In this case we sort the currencies into five instead of six baskets, to take into account the overall reduced number of currencies.

We calculate one-month bilateral log excess returns r_{t+1} as the sum of the interest differential and the rate of exchange rate depreciation of each currency with the US dollar:

$$r_{t+1} = i_t^\star - i_t - \Delta s_{t+1}, \tag{3}$$

where i^* and i are the foreign and US interest rate, respectively, and s_t is log spot exchange rate expressed in foreign currency per US dollar.

Fig. 2 shows that the sorting produces a monotonic increase in returns from Portfolios 1 to 6. Further descriptive statistics are reported in Table 1. Portfolios 6A and 6B highlight the different behavior of high inflation currencies. The standard deviation of returns for Portfolio 6B is almost double that of all other baskets. Bansal and Dahlquist (2000) note that the uncovered interest parity condition cannot be rejected for these currencies. These findings and the general concern about the effective tradability of these currencies during periods of economic turmoil lead us to present our benchmark results using only Basket 6A and to provide robustness checks including both Basket 6 and 6B in the online Appendix.

[4] It is in principle possible to allow both the concept of conditionality used in this paper and the time variation in betas and prices of risk to coexist within the same model. In the present context, this could be achieved by estimating time-varying betas and lambdas. Since this would require extracting additional information from a potentially limited number of observations for the downstate, we opt to impose constant betas and lambdas through time. While we do not disregard the possibility of time-varying parameters, we view our model choice as conservative given the available data and stress that this restriction is routinely imposed on asset pricing models, especially when testing them on sorted portfolios.

[5] We view our results excluding the high inflation currencies as conservative because these noisy observations are eliminated. Our results are robust to different threshold levels or to the inclusion of all the currencies in the sixth portfolio. The inflation data for all countries are from the International Monetary Fund International Financial Statistics.

[6] A country is considered developed if it is included in the MSCI World Market Equity Index.

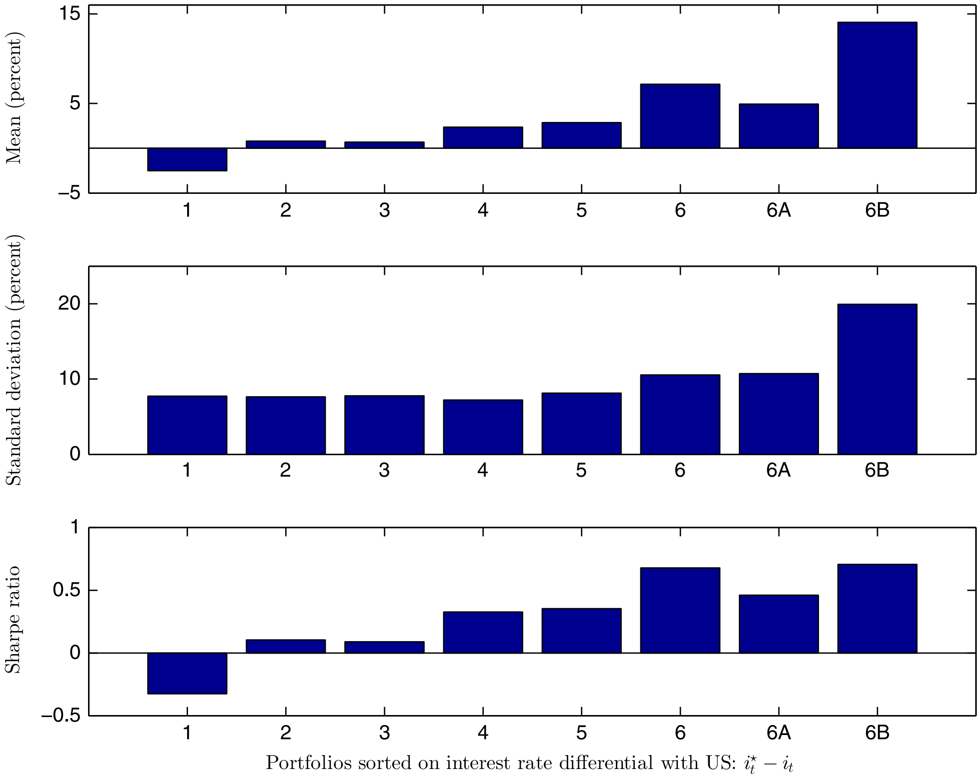

Fig. 2. Characteristics of the 6 currency portfolios.
Depicted are annualized mean excess returns, standard deviations, and Sharpe ratios for six currency portfolios, monthly re-sampled based on the interest rate differential with the US. High inflation countries in the last currency portfolio are subdivided into Basket 6B. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. The sample period is January 1974 to March 2010 for a total of 435 observations.

Table 1
Currency portfolios.
The table reports annualized sample means, standard deviations, and Sharpe ratios for the interest rate differentials, spot exchange rate changes, excess returns, and carry trade baskets for six currency portfolios, monthly re-sampled based on the interest rate differential with the US. High inflation countries in the last currency portfolio are subdivided into Basket 6B. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. The sample period is January 1974 to March 2010 for a total of 435 observations.

Interest rate differential	Low	2	3	4	5	High	6A	6B
Interest rate differential: $i^\star - i$								
Mean	−2.79	−0.56	1.11	2.97	5.59	22.01	12.58	36.02
Standard deviation	0.62	0.55	0.55	0.63	0.88	7.43	3.76	20.10
Spot change: Δs^j								
Mean	−0.27	−1.36	0.42	0.62	2.72	14.87	7.64	21.96
Standard deviation	7.63	7.56	7.70	7.19	8.11	10.27	11.30	15.87
Excess returns								
Mean	−2.52	0.79	0.69	2.35	2.87	7.14	4.94	14.06
Standard deviation	7.73	7.64	7.76	7.21	8.13	10.54	10.73	19.93
Sharpe ratio	−0.33	0.10	0.09	0.33	0.35	0.68	0.46	0.71
High minus low: $rx^j - rx^1$								
Mean		3.31	3.21	4.87	5.38	9.66	7.45	16.14
Standard deviation		4.59	5.43	5.30	6.17	10.50	10.31	20.23
Sharpe ratio		0.72	0.59	0.92	0.87	0.92	0.72	0.80

For our benchmark results on the cross section of equity returns, we use the six Fama and French portfolios sorted on size and book-to-market for the period from January 1974 to March 2010. In additional results we test our model on the cross section of industry-sorted equity portfolios by Fama and French for the period from January

1974 to March 2010, on the CAPM-beta sorted equity portfolios of Frazzini and Pedersen (2014) for the period from January 1974 to March 2010, and on the equity index option return series by Constantinides, Jackwerth, and Savov (2013) for the period from April 1986 to March 2010.

For the cross section of commodity returns we use five commodity futures portfolios sorted by the commodity basis for the period from January 1974 to December 2008 by Yang (2013). For the cross section of sovereign bonds we use six sovereign bond portfolios sorted by the probability of default as proxied by the credit rating (high credit rating parodying for low default probability) and bond beta for the period from January 1995 to March 2010 by Borri and Verdelhan (2011).

For the market return we use the value-weighted Center for Research in Security Prices (CRSP) US equity market log excess return for the period January 1974 to March 2010. We use a broad US equity market return as the market return in our benchmark results not only because it is the most commonly used return to test CAPM-like asset pricing models, but also to conservatively avoid increasing the covariances between test assets and pricing factors by including our test assets, such as currencies and commodities, in our market index. Nonetheless, in robustness checks included in the online Appendix we repeat our benchmark analysis using the MSCI World Market Equity Index returns and our own market index built by merging all our test assets in a single index.

Tables 2 and 3 provide summary statistics for the equity, equity index options, commodity futures, and sovereign bond portfolios returns. In Table 2, Panel A highlights the pattern that small and value stocks have higher returns; Panel B highlights that futures on commodities that have low basis have higher returns; Panel C highlights that sovereign bonds have higher returns whenever they have lower credit rating or higher CAPM betas or both. In Table 3, Panel A highlights that equities that have high preformation CAPM betas tend to earn (somewhat) lower returns; Panel B creates a cross section by sorting equities on their industry classification; Panels C and D, respectively, show that portfolios that are short equity index put options and long call options earn higher returns the further the options are out-of-the-money and the shorter the maturity for puts and the longer the maturity for calls.

2.2. *Conditional correlations*

The central insight underlying our work is that the currency carry trade, as well as other cross-sectional strategies, is more highly correlated with aggregate market

Table 2
Equity, commodity futures, and sovereign bond portfolios.

The table reports annualized sample means, standard deviations, and Sharpe ratios for portfolios of equity excess returns, commodity futures, and sovereign bond returns. Panel A reports the statistics for the six Fama and French portfolios sorted on size and book-to-market. Panel B reports the statistics for five commodity futures portfolios monthly re-sampled based on basis. Panel C reports the statistics for six sovereign bond portfolios monthly re-sampled based on the credit rating and bond beta. The sample period is January 1974 to March 2010 for a total of 435 observations in Panel A, January 1974 to December 2008 for a total of 420 observations in Panel B, and January 1995 to March 2010 for a total of 183 observations in Panel C.

	Mean	Standard deviation	Sharpe ratio
Panel A : Six Fama and French portfolios			
Small size			
Low book-to-market, portfolio 1	3.23	24.55	0.13
Medium book-to-market, portfolio 2	9.80	18.86	0.52
High book-to-market, portfolio 3	11.51	19.53	0.59
Big size			
Low book-to-market, portfolio 4	3.94	17.18	0.23
Medium book-to-market, portfolio 5	5.66	15.76	0.36
High book-to-market, portfolio 6	6.78	16.64	0.41
Panel B : Commodity futures portfolios			
Basis			
Low	9.18	18.50	0.50
2	5.70	15.65	0.36
3	3.59	16.38	0.22
4	0.32	15.58	0.02
High	−0.13	17.34	−0.01
Panel C : Sovereign bond portfolios			
Low bond beta			
High credit rating, portfolio 1	2.28	9.51	0.24
Medium credit rating, portfolio 2	4.43	10.96	0.40
Low credit rating, portfolio 3	6.80	16.36	0.42
High bond beta			
High credit rating, portfolio 4	7.45	9.27	0.80
Medium credit rating, portfolio 5	11.32	11.68	0.97
Low credit rating, portfolio 6	14.77	19.56	0.75

Table 3
Beta-sorted equities, industry, and equity index options portfolios.

This table reports annualized sample means, standard deviations, and Sharpe ratios for portfolios of equity excess returns, industry, and put and call option excess returns. Panel A reports the statistics for the five beta-sorted stock portfolios and a betting against beta (BAB) factor. Panel B reports the statistics for the five Fama and French industry portfolios. Panels C and D report the statistics for nine put and call option portfolios on the Standard & Poor's 500 with maturities between 30 and 90 days and moneyness between 90 and 110, respectively. The sample period is January 1974 to March 2010 for a total of 435 observations in Panels A and B and April 1986 to March 2010 for a total of 288 observations in Panels C and D.

	Mean	Standard deviation	Sharpe ratio
Panel A : CAPM beta – sorted equity portfolios			
Portfolio			
Low	12.40	14.47	0.86
2	13.20	18.08	0.73
3	12.06	20.17	0.60
4	12.05	23.23	0.52
High	10.46	30.16	0.35
BAB	11.97	12.18	0.98
Panel B : Fama and French industry portfolios			
Consumer, portfolio 1	6.20	16.43	0.38
Manufacturing, portfolio 2	5.60	15.66	0.36
High technology, portfolio 3	3.88	20.95	0.19
Health, portfolio 4	5.27	17.88	0.29
Other, portfolio 5	4.68	18.95	0.25
Panel C : Equity index put option portfolios			
Expiration 30, moneyness 90, portfolio 1	19.92	22.39	0.89
Expiration 30, moneyness 100, portfolio 2	6.93	17.79	0.39
Expiration 30, moneyness 110, portfolio 3	3.55	15.82	0.22
Expiration 60, moneyness 90, portfolio 4	12.16	21.23	0.57
Expiration 60, moneyness 100, portfolio 5	5.94	17.61	0.34
Expiration 60, moneyness 110, portfolio 6	3.07	16.09	0.19
Expiration 90, moneyness 90, portfolio 7	7.26	20.57	0.35
Expiration 90, moneyness 100, portfolio 8	5.05	17.60	0.29
Expiration 90, moneyness 110, portfolio 9	3.31	16.22	0.20
Panel D : Equity index call option portfolios			
Expiration 30, moneyness 90, portfolio 1	0.64	14.76	0.04
Expiration 30, moneyness 100, portfolio 2	−2.31	14.37	−0.16
Expiration 30, moneyness 110, portfolio 3	−5.05	13.60	−0.37
Expiration 60, moneyness 90, portfolio 4	0.78	14.61	0.05
Expiration 60, moneyness 100, portfolio 5	−1.76	14.42	−0.12
Expiration 60, moneyness 110, portfolio 6	−4.42	14.00	−0.32
Expiration 90, moneyness 90, portfolio 7	1.09	14.45	0.08
Expiration 90, moneyness 100, portfolio 8	−0.54	14.34	−0.04
Expiration 90, moneyness 110, portfolio 9	−2.25	14.41	−0.16

returns conditional on low aggregate returns than it is conditional on high aggregate market returns. This insight is supported by a growing empirical literature including Brunnermeier, Nagel, and Pedersen (2008), Burnside (2011a), Lustig and Verdelhan (2011), Christiansen, Ranaldo, and Soederlind (2011), and Mueller, Stathopoulos, and Vedolin (2012), all of which find a state dependent correlation. In ongoing work, Caballero and Doyle (2012) and Dobrynskaya (2014) highlight the strong correlation of the carry trade with market risk during market downturns. Our paper differs from all previous studies both by providing systematic evidence over a longer time period and larger sample of this state dependent correlation and by relating the resulting downside risk to that observed in other asset classes such as equities, equity index options, commodities, and sovereign portfolios.

We define the downstate to be months when the contemporaneous market return is more than 1 standard deviation below its sample average. A 1 standard deviation event is a reasonable compromise between a sufficiently low threshold to trigger concerns about downside risk and a sufficiently high threshold to have a large number of downstate observations in the sample. Our definition assigns 55 monthly observations to the downstate, out of 435 total observations in our sample. For robustness we test our model with different threshold levels as well as a finer division of the state space into three instead of two states.[7]

Table 4 shows that the carry trade is unconditionally positively correlated with market returns. As reported in the third row of the table, the unconditional correlation is 0.14 and statistically significant for our benchmark sample of currencies. Most of the unconditional correlation is due to the downstate. Conditional on the downstate the correlation increases to 0.33, while it is only 0.02 in the

[7] Thresholds of the sample average minus 0.5 or 1.5 standard deviations assign 118 observations and 27 observations to the downstate, respectively.

Table 4
Conditional correlations: carry trade and market excess returns.

The table reports correlations between the carry trade factor and the market excess return. The correlation are computed unconditionally, in the upstate and downstate as well as for various inflation thresholds. Newey and West standard errors are reported in parentheses. Downstates are all months in which the market return is more than 1 standard deviation below its sample mean. The upstate includes all observations that are not included in the downstate. The sample period is January 1974 to March 2010 for a total of 435 observations.

	All	Downstate	Upstate
All countries	0.12	0.26	0.05
	(0.04)	(0.19)	(0.06)
Excluding high inflation (5%)	0.08	0.28	0.00
	(0.04)	(0.22)	(0.05)
Excluding high inflation (10%)	0.14	0.33	0.02
	(0.05)	(0.19)	(0.05)
Excluding high inflation (15%)	0.15	0.41	0.02
	(0.05)	(0.22)	(0.05)
Developed countries	0.23	0.31	0.10
	(0.07)	(0.15)	(0.06)

upstate.[8] The table also confirms that this pattern is robust to the exclusion of emerging markets and to various thresholds of inflation for the Basket 6B.

Fig. 3 highlights this characteristic of the data by plotting the kernel-smoothed conditional correlation between the carry trade and the market returns. The top panel shows that the correlation of high-yield currencies with the market returns is a decreasing function of market returns. The opposite is true for low-yield currencies in the middle panel. The bottom panel highlights that our results are not sensitive to the exact choice of threshold.

3. Econometric model

We estimate the model in Eq. (1) with the two-stage procedure of Fama and MacBeth (1973). In our model the first stage consists of two time series regressions, one for the entire time series and one for the downstate observations. These regressions produce point estimates for the unconditional and downstate betas, $\hat{\beta}$ and $\hat{\beta}^-$, which are then used as explanatory variables in the second stage. The second-stage regression is a cross-sectional regression of the average return of the assets on their unconditional and downstate betas. In our estimation we restrict, following the theory section above, the market price of risk to equal the sample average of the market excess return. Therefore, in the second-stage regression we estimate a single parameter: the downside price of risk λ^-.

Formally, the first-stage regressions are

$$r_{it} = a_i + \beta_i r_{mt} + \epsilon_{it}, \quad \forall t \in T, \tag{4}$$

and

$$r_{it} = a_i^- + \beta_i^- r_{mt} + \epsilon_{it}^- \quad \text{whenever } r_{mt} \le \bar{r}_m - \sigma_{r_m}, \tag{5}$$

where $\bar{r}_m$ and σ_{r_m} are the sample average and standard deviation of the market excess return, respectively. The second-stage regression is given by

$$\bar{r}_i = \hat{\beta}_i \bar{r}_m + (\hat{\beta}_i^- - \hat{\beta}_i)\lambda^- + \alpha_i, \quad i = 1, \ldots, N, \tag{6}$$

where $\bar{r}_i$ and $\bar{r}_m$ are the average excess returns of the test assets and the market excess return, respectively; α_i are pricing errors; and N is the number of test assets. By not including a constant in the second-stage regression we are imposing that an asset with zero beta with the risk factors has a zero excess return.[9]

While restricting the model so that the market return is exactly priced reduces the number of coefficients to be estimated in the cross-sectional regression, it does not imply that the sample average market return is estimated without noise. The average monthly log excess return of the value-weighted CRSP US equity market for the sample period from January 1974 to March 2010 is 0.39% with a standard error of 0.23%.[10] This corresponds to an annualized log-excess return for the market of 4.68%, an estimate in the range of the values usually assumed to calibrate the equity premium. To make clear that the unconditional market price of risk is imposed instead of estimated in our cross-sectional regressions, we report its estimate with a star and do not report its standard error in all tables of the paper. While restricting the market to be exactly priced is regarded as a conservative procedure, we report in the online Appendix our benchmark results for currencies, commodities, and equities without imposing this restriction and we recover an estimate of the price of unconditional market risk of 0.29 that is similar to the sample average estimate of 0.32.

4. Empirical results

We provide here the empirical estimates of the model described above on a number of different asset classes.

4.1. Risk premia: currency

We find that while the CAPM shows that currency returns are associated with market risk, it cannot explain the cross section of currency returns because the CAPM beta is not sufficient to explain the cross-sectional dispersion in returns. The left panel of Fig. 4 shows that the increase in CAPM beta going from the low-yield portfolio (Portfolio 1) to the high-yield portfolio (Portfolio 6) is small compared with the increase in average returns for these portfolios. As shortly becomes evident, once the market price of risk of CAPM is pinned down by the

[8] The upstate includes all observations that are not included in the downstate.

[9] In unreported results we estimate the model including a constant in the cross-sectional regression and verify that the constant is not statistically significant and economically small.

[10] When estimating the model on subperiods, we always impose that the average market return over that subperiod is priced exactly by correspondingly adjusting the value of *lambda*.

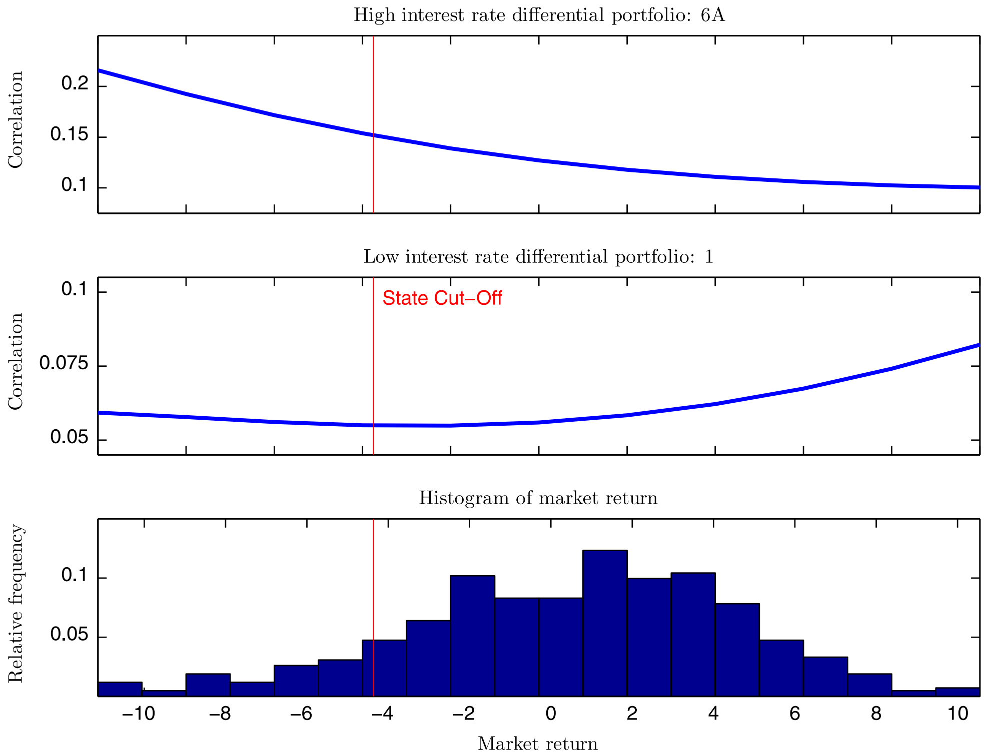

Fig. 3. Kernel-smoothed conditional correlation.
Depicted are the kernel-smoothed estimate of the conditional correlation between different currency portfolios and the market excess return conditional on the market excess return using a normal kernel. The top panel depicts the correlation of the market excess return with the high interest rate currencies (Portfolio 6A). The middle panel depicts the correlation of the market excess return with the low interest rate currencies (Portfolio 1). The bottom panel depicts the empirical distribution of market excess returns. High inflation countries in the last portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. The vertical line indicates the state cut-off in the empirical analysis of 1 standard deviation below the mean of the market excess return. The graphs have been cut on the left and right at $\mp$ 10% monthly market excess return. The sample period is January 1974 to March 2010 for a total of 435 observations.

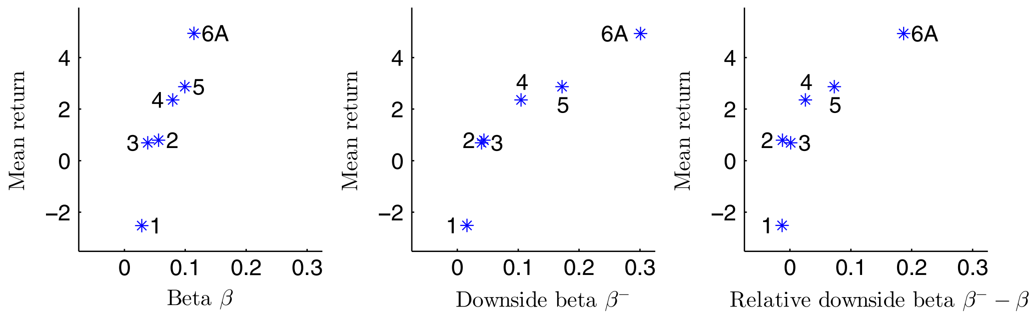

Fig. 4. Risk–return relations: currencies.
Depicted are risk–return relations for six currency portfolios (1 to 6A), monthly re-sampled based on the interest rate differential with the US. High inflation countries in the last portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. From left to right, the panels plot the realized mean excess return versus the capital asset pricing model betas (β), the downside betas (β^-), and the relative downside betas ($\beta^- - \beta$). The sample period is January 1974 to March 2010 for a total of 435 observations.

average market excess return, the CAPM fails to price these currency portfolios.

The middle panel of Fig. 4 shows that average currency returns are also strongly related to the downstate beta. While this finding supports the importance of downside risk for currency returns, it is not per se evidence of a failure of the CAPM because currencies that have a higher downstate beta do have a higher CAPM beta.

However, the right panel of Fig. 4 shows that the relative downstate beta, the difference between downstate and unconditional beta, is also associated with contemporaneous returns. Currencies that have higher downstate than unconditional betas are on average riskier and earn higher excess returns. We show in our benchmark regressions that this state dependency is not fully captured by the CAPM beta.

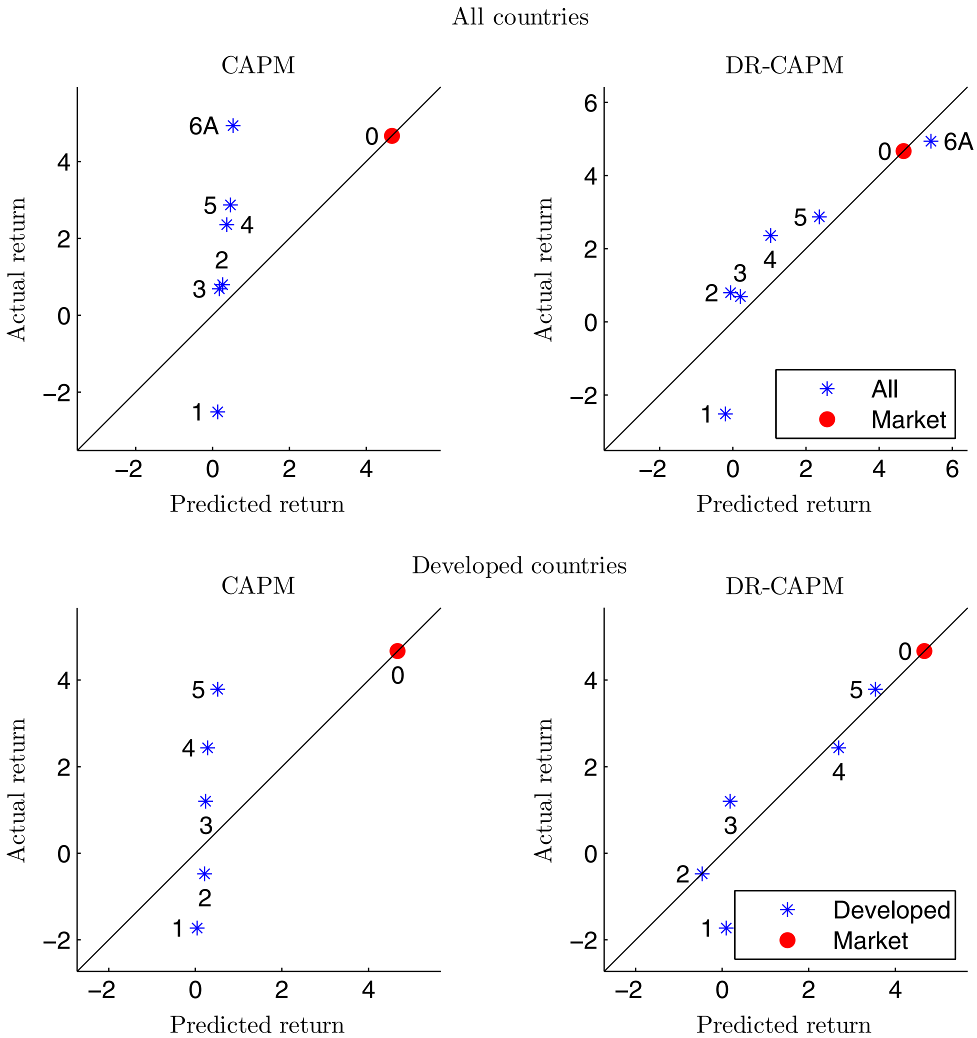

Fig. 5. Model performance: currencies.
Depicted are annualized mean excess returns versus the predicted excess returns in percent for the unconditional capital asset pricing model (CAPM) in the left panels and the downside risk CAPM (DR-CAPM) in the right panels. In the top panels, test assets are six currency portfolios (1 to 6A), monthly re-sampled based on the interest rate differential with the US. High inflation countries in the last portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. In the bottom panels, test assets are five currency portfolios of developed countries. The market excess return is included as a test asset (0). The sample period is January 1974 to March 2010 for a total of 435 observations.

Fig. 5 and Table 5 illustrate both the failure of the CAPM and the performance of the DR-CAPM. The top panels of Fig. 5 present the results employing all currencies, and the bottom panels present the results employing only currencies of developed countries. Since higher-yield currencies have higher CAPM betas, they earn a higher return on average. However, the CAPM beta does not fully capture the risk–return trade-off. The spread in betas is too small to account for the spread in currency returns. The failure is evident in the first column of Table 5, where the CAPM cannot jointly price the market return and the cross section of currency returns producing a R^2 of only 9%.[11] Correspondingly, the left panels of Fig. 5 show that the CAPM predicts almost identical returns for all currency portfolios.

In contrast, the DR-CAPM explains the cross section of currency returns. In the second column of Table 5, the DR-CAPM explains 79% of the cross-sectional variation in mean returns even after imposing the restriction that the market portfolio (included as a test asset) is exactly priced. The right quadrants of Fig. 5 correspondingly show that the test assets lie close to the 45 degree line. The estimated price of downside risk is positive (2.18) and statistically significant.[12] The model fits the returns of Portfolios 2 to

[11] We define the cross-sectional R^2 as $R^2 \equiv 1-\hat{\alpha}'\hat{\alpha}[N\,Var(r)]^{-1}$, where $\hat{\alpha}$ is the vector of pricing errors, $Var(r)$ is the variance of the vector of test assets' mean returns, and N is the number of test assets.

[12] The Fama and MacBeth procedure does not automatically correct the second-stage regression standard errors for estimated regressors from the first-stage. Given our separate first-stage regressions for the full sample and the downstate, the Shanken correction (Shanken, 1992) is not

Table 5
Estimation of linear pricing models: currencies and equities.

The table reports prices of risk, Fama and MacBeth standard errors in parentheses, χ^2 statistics testing for joint significance of pricing errors, root mean squared pricing errors (RMSPE), the number of observations T and the cross sectional R^2's for the unconditional capital asset pricing model (CAPM) and the downside risk CAPM (DR-CAPM). In Columns 1 and 2, test assets are six currency portfolios, monthly re-sampled based on the interest rate differential with the US. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. Columns 3 and 4 use five currency portfolios of developed countries as test assets, and Columns 5 and 6 add the six Fama and French portfolios sorted on size and bool-to-market to the six currency portfolios. The market excess return is included as a test asset. The sample period is January 1974 to March 2010 for a total of 435 observations. Starred estimates impose the restriction that the market excess return is exactly priced and consequently no standard errors are reported.

	All currencies		Developed currencies		Currencies and equities	
	CAPM (1)	DR-CAPM (2)	CAPM (3)	DR-CAPM (4)	CAPM (5)	DR-CAPM (5)
λ	0.39*	0.39*	0.39*	0.39*	0.39*	0.39*
λ^-		2.18		2.34		1.41
		(0.77)		(1.05)		(0.40)
χ^2	42.28	24.60	22.36	9.81	114.54	63.39
P-value	0.00%	0.04%	0.10%	8.09%	0.00%	0.00%
RMSPE	0.19	0.09	0.15	0.07	0.26	0.16
R^2	8.77%	78.74%	34.74%	85.32%	24.31%	71.41%
T	435	435	435	435	435	435

6A with small pricing errors. The absolute pricing error is on average 0.07% (in terms of monthly excess returns) across these portfolios. Portfolio 1, which contains the low-yield currencies, is priced with the biggest pricing error, −0.2%.[13] We also report the χ^2 test that all pricing errors in the cross-sectional regression are jointly zero. While both the CAPM and the DR-CAPM are formally rejected with p-values of 0% and 0.04%, respectively, the DR-CAPM produces a root mean square pricing error (RMSPE) that is 40% smaller than that of the CAPM.[14]

Potential sources of concern about the reliability of our currency returns are sovereign default and international capital restrictions. To alleviate these concerns, we test the DR-CAPM on a subsample of developed countries' currencies. The results for this subsample of countries are also reported in Fig. 5 and Table 5 and show that the model performs equally well on these portfolios. The price of downside risk is 2.34 and is consistent with the 2.18 estimate obtained on the full sample. The R^2 increases to 85%. We confirm on this subsample the pattern of small DR-CAPM pricing errors for all portfolios except Portfolio 1. The null hypothesis of zero joint pricing errors cannot be rejected at the 5% confidence level with a p-value of the χ^2 test of 8%. The RMSPE of 0.07 is more than 50% smaller than the one produced by the CAPM on the same test assets.

4.2. Risk premia: other asset classes

The conditional association of asset returns and the market portfolio and the variation in prices of risk is not unique to currencies and is, in fact, shared by other asset classes. Providing a unified risk-based treatment of expected returns across asset classes is both informative from a theoretical perspective and an important check of the empirical performance of theoretical models.

Fig. 6 shows that equity, commodity, and sovereign bond portfolios' expected returns are positively related to these assets' relative downside betas. In all three asset classes, assets that are more strongly associated with market returns conditional on the downstate than unconditionally have higher average excess returns. This conditional variation, which is not captured by the CAPM, is the central mechanism that underlies the performance of the DR-CAPM across asset classes.

We investigate next whether the DR-CAPM can jointly explain the cross section of currency and equity returns. We add the six Fama and French portfolios sorted on book-to-market and size to the currency and market portfolios as test assets. Fig. 7 and Table 5 show that the DR-CAPM jointly explains these returns. The last column in Table 5 shows that the estimated price of downside risk is consistent across asset classes but the estimate of 1.41 is lower than that obtained on currencies alone (2.18).[15] The model explains 71% of the observed variation in mean returns, a noticeable increase over the 24% explained by the CAPM. Fig. 7 shows that the largest pricing errors occur for the small-growth equity portfolio (Portfolio 7) in addition to the low-yield currency portfolio (Portfolio 1). The average absolute pricing error on all other portfolios is 0.08%, and the pricing errors on the low yield currency portfolio and the small growth equity portfolios are −0.2% and −0.47%, respectively. Section 6.2 provides further details about the pricing of the small-growth equity portfolio. Both the CAPM and the DR-CAPM are statistically rejected with p-values of the χ^2 test of 0%, but the DR-CAPM produces a RMSPE 40% smaller than the CAPM.

A close analog to the currency carry trade is the basis trade in commodity markets. The basis is the difference between the futures price and the spot price of a commodity. Among others, Yang (2013) shows that commodities with a lower basis earn higher expected returns (see

(*footnote continued*)
immediately applicable here. In the robustness section of this paper, Section 5, and in the online Appendix, we provide a number of checks of the standard errors to minimize concerns about their accuracy.

[13] The pricing errors here and in all subsequent tables and references in the text are expressed in monthly percentage excess returns, while the figures are annualized percentage excess returns. The pricing errors are defined as the difference between the actual and model-predicted excess return, so that a positive price error corresponds to an underprediction of the excess return by the model.

[14] The test is under the null hypothesis of zero joint pricing errors. Therefore, the model is not rejected at the 5% confidence level if the p-value statistic is higher than 5%.

[15] If the small-growth equity portfolio is excluded as a test asset, the estimated price of downside risk increases to 1.70.

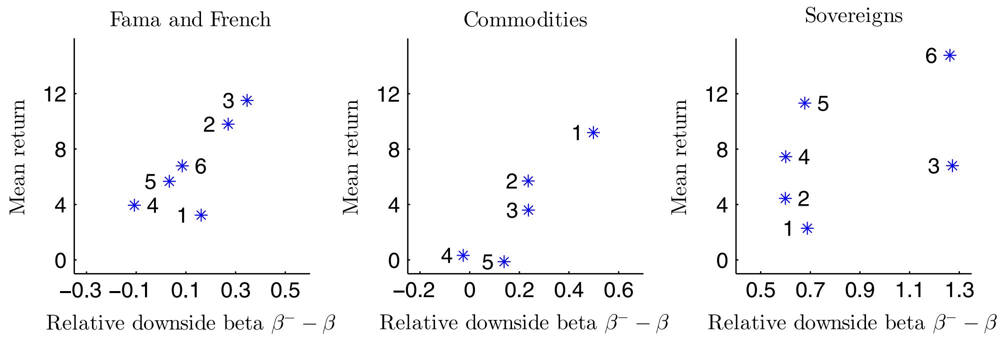

Fig. 6. Risk–return relations: other asset classes.
Depicted are risk–return relations for the six Fama and French portfolios sorted on size and book-to-market (left panel), five commodity futures portfolios monthly re-sampled based on basis (middle panel), and six sovereign bond portfolios monthly re-sampled based on their credit rating and bond beta (right panel). The panels plot the realized mean excess return versus the relative downside betas ($\beta^- - \beta$). The sample period is January 1974 to March 2010 for a total of 435 observations for the equity portfolios, January 1974 to December 2008 for a total of 420 observations for the commodity portfolios, and January 1995 to March 2010 for a total of 183 observations for the sovereign bond portfolios.

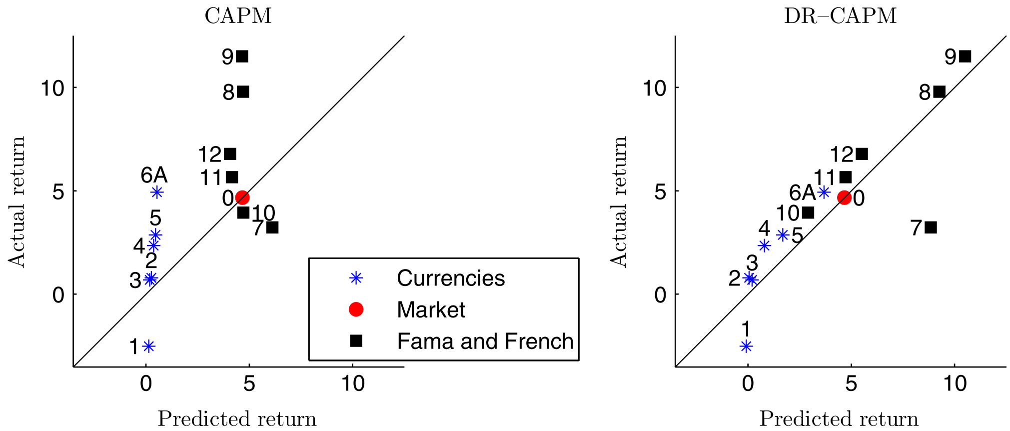

Fig. 7. Model performance: currencies and equities.
Depicted are annualized mean excess returns versus the predicted excess returns in percent for the unconditional capital asset pricing model (CAPM) in the left panel and the downside risk CAPM (DR-CAPM) in the right panel. Test assets are six currency portfolios (1 to 6A), monthly re-sampled based on the interest rate differential with the US as well as the six Fama and French equity portfolios sorted on size and book-to-market (7 to 12). The market excess return is included as a test asset (0). High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. The sample period is January 1974 to March 2010 for a total of 435 observations.

Table 2, Panel B).[16] We extend our results by adding the commodity portfolios to the currency and equity portfolios. Fig. 8 and Table 6 show that the same economic phenomenon, the conditional variation of the quantity and price of market risk, underlies the variation in expected returns in commodity markets. The fourth column in Table 6 shows that the estimated price of downside risk (1.40) is essentially unchanged after the addition of the commodity portfolios to the currency and equity portfolios studied above and is statistically significant. The model explains 74% of the cross-sectional variation in returns across these asset classes compared with a R^2 of −17% for the CAPM. The biggest pricing error occurs for the high-basis commodity portfolio (Portfolio 11) in addition to the low-yield currency portfolio (Portfolio 1) and the small-growth equity portfolio (Portfolio 12). The pricing errors for these three portfolios are −0.24%, −0.22%, and −0.46%, respectively. The average absolute pricing error of all other portfolios included as test assets is 0.07%. While both the CAPM and the DR-CAPM are again statistically rejected, the DR-CAPM produces a RMSPE 50% smaller than the CAPM.

We investigate next whether sovereign bonds are priced by the DR-CAPM. We use the cross-sectional sorting of sovereign bonds according to default probability and market beta in Borri and Verdelhan (2011). Fig. 9 and Table 6 confirm yet again the ability of the DR-CAPM to price multiple asset classes. An important caveat in this case is that the data of Borri and Verdelhan (2011) are available only over a relatively short sample period (January 1995 to March 2010), thus limiting the number of observations, particularly for our downstate. The shorter sample produces noisier estimates of the prices of risk and different point estimates overall from our full sample. The sample limitations impose caution in interpreting the positive performance of our model on sovereign bonds. Consequently, we exclude these portfolios from the analysis in the rest of the paper.

[16] See also Gorton, Hayashi, and Rouwenhorst (2013).

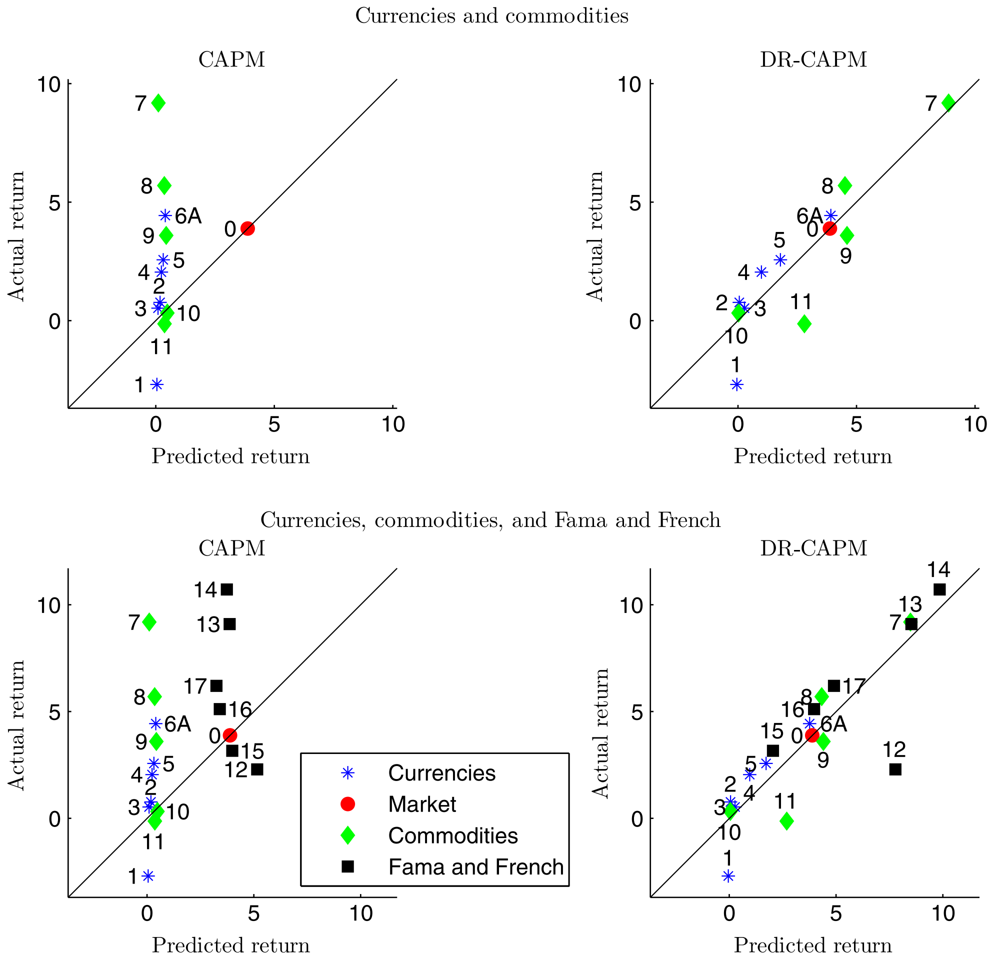

Fig. 8. Model performance: currencies, equities, and commodities.
Depicted are annualized mean excess returns versus the predicted excess returns in percent for the unconditional capital asset pricing model (CAPM) in the left panels and the downside risk CAPM (DR-CAPM) in the right panels for six currency portfolios (1 to 6A), monthly re-sampled based on the interest rate differential with the US, five commodity futures portfolios monthly re-sampled based on basis (7 to 11) as well as the six Fama and French portfolios sorted on size and book-to-market (12 to 17). The market excess return is included as a test asset (0). High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has an annualized monthly inflation of 10% higher than US inflation. The sample period is January 1974 to December 2008 for a total of 420 observations.

In our benchmark results for equity markets we employ the Fama and French book-to-market and size-sorted portfolios because they are among the most commonly tested equity cross sections. In addition, we show here that the DR-CAPM can rationalize a number of other important cross sections in equity markets: the CAPM beta-sorted cross section, the industry-sorted cross section, and the equity index options cross section.

In Fig. 10 and Table 7 we analyze the performance of the DR-CAPM for the cross section of CAPM beta-sorted equity portfolios of Frazzini and Pedersen (2014) as well as for their betting against beta (BAB) factor for equity markets.[17] The DR-CAPM has higher explanatory power than the CAPM for the joint cross section of currency, commodity, and beta-sorted equity returns with estimates of the market price of downside risk consistent with those estimated on other cross sections. The BAB factor has a 1.03% pricing error under the CAPM that is almost seven times bigger than the 0.15% pricing error under the DR-CAPM.

We show that for the cross section of currencies, commodities, and Fama and French portfolios the CAPM underpredicts the excess returns and the downside risk factor is able to fill the gap between the CAPM-predicted excess returns and the actual excess returns in the data. Interestingly, for the beta-sorted portfolios CAPM over-predicts the returns of the high-beta portfolios with respect to the low-beta portfolios; a fact that Frazzini and Pedersen (2014) refer to as a “too flat” Security Market Line in the data. The DR-CAPM in part corrects the over-prediction of the CAPM because high-beta equities have a relatively lower downside risk exposure compared with low-beta equities. For example, consider the BAB factor in the top panels of Fig. 10. By construction it has a CAPM beta close to zero, estimated at −0.05 and not statistically significant, and its riskiness is entirely captured by its downside beta, estimated at 0.48 and

[17] The BAB factor is built via a long position in low beta equities and a corresponding short position in high beta equities. See original reference for details.

Table 6

Estimation of linear pricing models: currencies, equities, commodities, and sovereigns.

This table reports prices of risk, Fama and MacBeth standard errors in parentheses, χ^2 statistics testing for joint significance of pricing errors, root mean squared pricing errors (RMSPE), the number of observations T and the cross sectional R^2's for the unconditional capital asset pricing model (CAPM) and the downside risk CAPM (DR-CAPM). In Columns 1 and 2, test assets are six currency portfolios, monthly re-sampled based on the interest rate differential with the US and five commodity futures portfolios, monthly re-sampled based on basis. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. Columns 3 and 4 add the six Fama and French portfolios, sorted on size and book-to-market. Columns 5 and 6 use the six currency portfolios and six sovereign bond portfolios, monthly re-sampled based on the credit rating and bond beta as test assets. Columns 7 and 8 add the six Fama and French portfolios, sorted on size and book-to-market. The market excess return is included as a test asset. The sample period is January 1974 to December 2008 for a total of 420 observations in Columns 1 to 4, and January 1995 to March 2010 for a total of 183 observations in Columns 5 to 8. Starred estimates impose the restriction that the market excess return is exactly priced and consequently no standard errors are reported.

	Currencies and commodities		Equities, currencies, and commodities		Currencies and sovereigns		Equities, currencies, and sovereigns	
	CAPM	DR-CAPM	CAPM	DR-CAPM	CAPM	DR-CAPM	CAPM	DR-CAPM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ	0.32*	0.32*	0.32*	0.32*	0.41*	0.41*	0.41*	0.41*
λ^-		1.47		1.40		0.53		0.56
		(0.53)		(0.38)		(0.21)		(0.21)
χ^2	52.66	28.24	128.27	64.48	40.26	39.68	88.31	86.54
P-value	0.00%	0.30%	0.00%	0.00%	0.01%	0.01%	0.00%	0.00%
RMSPE	0.30	0.11	0.31	0.15	0.41	0.22	0.38	0.22
R^2	−42.93%	80.69%	−17.38%	73.52%	−20.81%	65.80%	−22.66%	57.10%
T	420	420	420	420	183	183	183	183

statistically significant (see Panel A, Table 8).[18] Therefore, for the BAB portfolio the CAPM implies an annualized expected excess return of −0.19%, and the DR-CAPM predicts an excess return of 10.3%, which is substantially closer to the actual average excess return of 12.13%.[19] This result is consistent with the analysis in Frazzini and Pedersen (2014) who note that the BAB factor performs particularly poorly when the overall market return is low, thus naturally generating a downside risk exposure.

In Fig. 11 and Table 7 we test the DR-CAPM on the industry-sorted equity portfolios of Fama and French jointly with the currency and commodity portfolios. We consistently find that the DR-CAPM can rationalize these test assets with a price of downside risk, here estimated at 1.36, similar to that estimated on other cross sections. The last column in Table 7 shows that the model explains 75% of the joint variation in returns of currencies and equity industry portfolios with a substantial increase over the −32% explained by the CAPM.

Finally, we investigate whether the DR-CAPM can rationalize option returns. Options, and in particular portfolios short in put options written on the market index, are naturally exposed to downside risk. We test the model on the cross section of equity index (Standard & Poor's 500) option returns in Constantinides, Jackwerth, and Savov (2013).[20] Fig. 12 and Table 9 present the results based on the cross section of call and put options. The second column in Table 9 shows that the DR-CAPM not only captures 81% of the variation in expected returns across option portfolios, but can also jointly rationalize this variation together with the returns of currencies and commodities (R^2 of 74%; see Column 4 of the same table). This further confirms that the estimated value of the price of downside risk (λ^-) is consistent across asset classes even when considering optionality features.

In contrast, the CAPM cannot rationalize option returns. By construction the option portfolios have a CAPM beta close to one (see Panels C and D, Table 8), thus generating almost identical CAPM-predicted returns for all portfolios, but have substantial variation in realized average excess returns (close to a 25% range).[21] Almost all option portfolios are accurately priced with small pricing errors with the exception of the 30-day maturity and 90% moneyness put portfolio.[22] Constantinides, Jackwerth, and Savov (2013) report that this portfolio is hard to price even for most option market-tailored asset pricing models and consider the possibility that liquidity issues might affect its pricing.

We show that the DR-CAPM can rationalize a number of important asset classes and that the estimate of the price of risk remains stable across different estimations.

[18] Frazzini and Pedersen (2014) build the BAB factor to have zero CAPM beta. Small differences in the beta occur here because of the use of a different index to proxy for the CAPM market portfolio as well as a different time period.

[19] The CAPM prediction is obtained by multiplying the beta by the market price of risk ($-0.05*0.32*12=-0.19$). Similarly, the DR-CAPM prediction is obtained by summing to the CAPM prediction the downside risk correction of $(\beta^- - \beta)\lambda^- *12=(0.48+0.05)1.65*12=10.49$.

[20] The cross section includes 18 portfolios of calls (nine) and puts (nine) sorted on maturity and in-the-moneyness. See original source for portfolio construction details.

[21] Constantinides, Jackwerth, and Savov (2013) build the option portfolios by imposing that under the Black and Scholes assumptions they would have a CAPM beta of one with the S&P 500 index. The variation in CAPM betas reported here with respect to the original source is due to the use of the value-weighted CRSP as a market index as well as a different time period for the sample.

[22] This is the shortest maturity and furthest out-of-the-money portfolio in the sample.

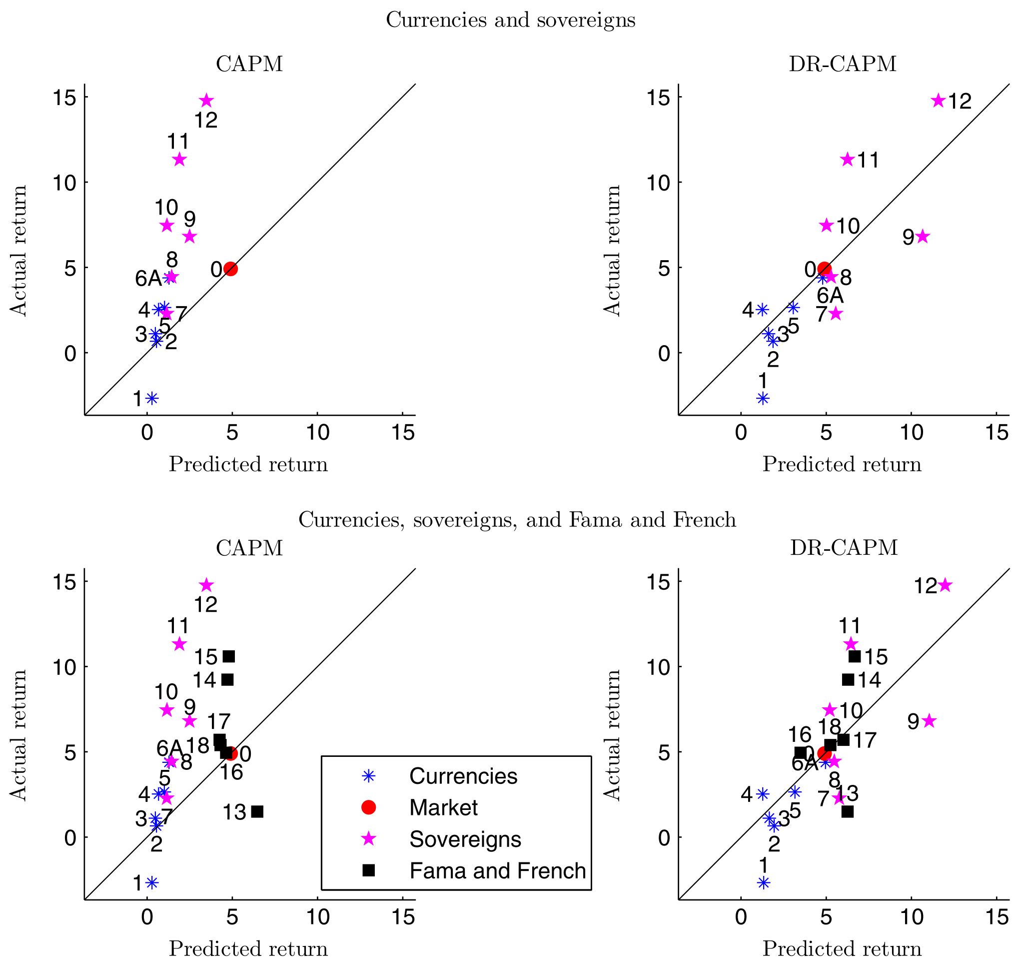

Fig. 9. Model performance: currencies, equities, and sovereign bonds.
Depicted are annualized mean excess returns versus the predicted excess returns in percent for the unconditional capital asset pricing model (CAPM) in the left panels and the downside risk CAPM (DR-CAPM) in the right panels for six currency portfolios (1 to 6A), monthly re-sampled based on the interest rate differential with the US, six sovereign bond portfolios monthly re-sampled based on their credit rating and bond beta (7 to 12) as well as the six Fama and French portfolios sorted on size and book-to-market (13 to 18). The market excess return is included as a test asset (0). High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has an annualized monthly inflation of 10% higher than US inflation. The sample period is January 1995 to March 2010 for a total of 183 observations.

While this reduces concerns about the reliability of estimates of λ^-, further quantitative implications of our empirical framework, for example, about the magnitude of λ^-, cannot be drawn without imposing a more structural theory on the model. We leave the development of a structural theory to future work and note here only that λ^- is consistently estimated across a number of !cross sections, asset classes and patterns in expected returns.[23]

[23] Ultimately, the quantitative importance of downside risk could also be linked to the rare disasters model of Barro (2006). Farhi and Gabaix (2008) develop a model of exchange rates in the presence of rare disasters, and Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan, (2012) and Jurek (2014) evaluate rare disasters in currency markets in an option framework.

5. Robustness

An important verification of our results is to confirm the association of currency returns with downside market risk. In Panel A of Table 10 we provide the first-stage estimates of the unconditional CAPM betas and the downstate betas for the six currency portfolios. The CAPM betas are increasing from Portfolio 1 to 6, and the spread in betas between the first and last portfolio is statistically different from zero. The increase in betas, however, is small. The beta of the first portfolio is 0.03, and the beta of the last portfolio is 0.11. The downstate betas highlight the central mechanism of the DR-CAPM. Conditional on below-threshold market returns, high-yield currencies (Portfolio 6A) are more strongly related to market risk than low-yield currencies (Portfolio 1). In fact, we find that while the downside beta of Portfolio 6A (0.30) is larger than its unconditional beta (0.11), the opposite is true for Portfolio 1 with a downside beta of 0.02 and an unconditional beta of 0.03.

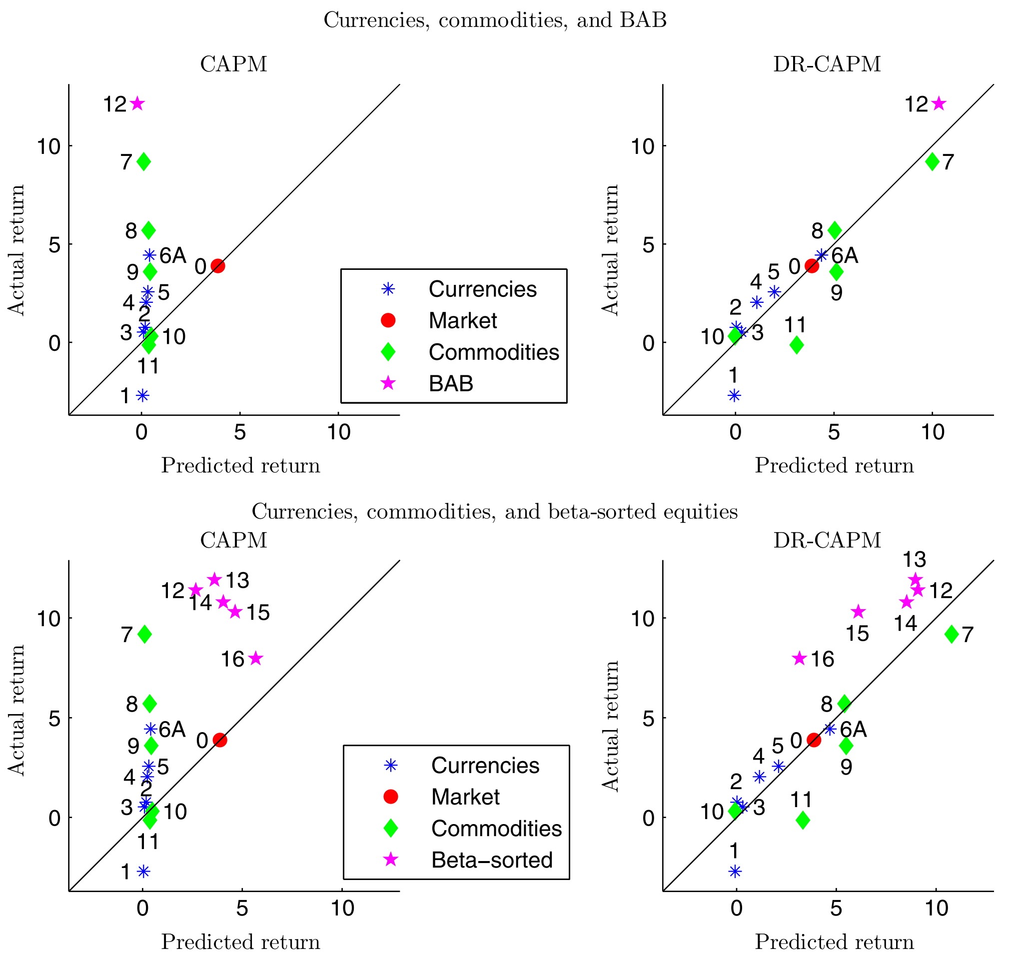

Fig. 10. Model performance: currencies, commodities, and beta-sorted equities.
Depicted are annualized mean excess returns versus the predicted excess returns in percent for the unconditional capital asset pricing model (CAPM) in the left panels and the downside risk CAPM (DR-CAPM) in the right panels for six currency portfolios (1 to 6A), monthly re-sampled based on the interest rate differential with the US, five commodity futures portfolios monthly re-sampled based on basis (7 to 11) as well as the betting against beta (BAB) factor (12) in the top panels and five portfolios sorted on CAPM beta (12 to 16) in the bottom panels. The market excess return is included as a test asset (0). High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has an annualized monthly inflation of 10% higher than US inflation. The sample period is January 1974 to December 2008 for a total of 420 observations.

Splitting the sample into downstates and upstates picks up the conditional variation in currencies' association with market risk but also reduces the variation available in each subsample to estimate the betas. Therefore, the standard errors of the first-stage regressions that estimate downstate betas are wider than those of the corresponding regressions for unconditional betas. We perform a number of robustness checks of our first-stage estimates and their impact on the second-stage estimates.

We perform two bootstrap tests to check the robustness of the main driver of our results: the different conditional association of high-yield and low-yield currencies with the market excess return. We first test whether high-yield currencies are more associated with market risk than low-yield currencies conditional on the downstate under the null hypothesis that $\beta_{6A}^- - \beta_1^- = 0$. We then test whether the different loading on risk of high- and low-yield currencies varies across states under the null hypothesis that $(\beta_{6A}^- - \beta_1^-) - (\beta_{6A} - \beta_1) = 0$. Fig. 13 shows that both nulls are strongly rejected with p-values of 0.26% and 2.47%, respectively, thus yielding statistical support for our main economic mechanism.

A second robustness check is to mitigate the concern that our second-stage regression employs potentially weak estimated regressors from the first stage. Panel B in Table 10 reports the first-stage estimates for the six Fama and French equity portfolios. Since these equity portfolios have a strong association with the overall equity market, the betas are precisely estimated even for the downstate. We then use the prices of risk estimated using only these equity portfolios to fit the cross section of currencies. Table 11 reports in the first two columns that the DR-CAPM can still explain 67% of the observed variation in currency returns and 71% of the variation in currency and equity returns. The estimated price of downside risk is 1.27, statistically significant, and consistent with the

Table 7
Estimation of linear pricing models: currencies, commodities, and beta-sorted and industry-sorted equities.
This table reports prices of risk, Fama and MacBeth standard errors in parentheses, χ^2 statistics testing for joint significance of pricing errors, root mean squared pricing errors (RMSPE), the number of observations T and the cross sectional R^2's for the unconditional capital asset pricing model (CAPM) and the downside risk CAPM (DR-CAPM). In Columns 1 and 2, test assets are six currency portfolios, monthly re-sampled based on the interest rate differential with the US, five commodity futures portfolios, monthly re-sampled based on basis as well as a betting against beta (BAB) factor. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. Columns 3 and 4 use five portfolios sorted on CAPM beta instead of the BAB factor. Columns 5 and 6 add the five Fama and French industry portfolios to the currency and commodity portfolios. The market excess return is included as a test asset. The sample period is January 1974 to December 2008 for a total of 420 observations. Starred estimates impose the restriction that the market excess return is exactly priced and consequently no standard errors are reported.

	BAB, currencies, and commodities		Beta-sorted equities, currencies, and commodities		Industry-sorted equities, currencies, and commodities	
	CAPM	DR-CAPM	CAPM	DR-CAPM	CAPM	DR-CAPM
	(1)	(2)	(3)	(4)	(5)	(6)
λ	0.32*	0.32*	0.32*	0.32*	0.32*	0.32*
λ^-		1.65		1.78		1.36
		(0.35)		(0.39)		(0.45)
χ^2	91.04	28.49	102.75	41.85	62.11	38.96
P-value	0.00%	0.47%	0.00%	0.04%	0.00%	0.01%
RMSPE	0.40	0.12	0.39	0.19	0.26	0.11
R^2	−58.66%	86.45%	−12.10%	74.55%	−32.80%	75.02%
T	420	420	420	420	420	420

estimate of 1.41 obtained on the joint sample of currencies and equities.[24]

In the middle two columns of Table 11 we verify that our results are not altered by reasonable variations in the threshold for the downstate. We vary our benchmark threshold for the market return of 1 standard deviation below its sample mean to 0.5 and 1.5 standard deviations. In both cases we observe a consistent performance of the model.

Finally, we verify the sensitivity of our results to different thresholds for excluding currencies with high inflation. We vary the inflation threshold from our benchmark of 10% above the annualized inflation of the US to 5% and 15%. The last two columns of Table 11 show that the lower inflation threshold produces higher but noisier estimates of the price of risk compared with the higher threshold. In both cases, however, the prices of risk are statistically significant, in line with previous estimates, and the R^2's are around 80%.

Further robustness checks are provided in the online Appendix. We verify that our results are robust to using only developed countries' currencies, winsorizing the data, not imposing the restriction that the market return be exactly priced in sample, alternative measures of the market index, estimating the model on a longer sample (and relative subsamples) for equity markets, and using the model specification in Ang, Chen, and Xing (2006).

6. Factor structure and PCA-based models

To further investigate the common factor structure in the joint cross section of currencies, equities, and commodities, we perform a principal component analysis both on each asset class separately and on their joint returns. This analysis allows us to compare the DR-CAPM with the asset class-specific PCA-based models that are prevalent in the literature.

6.1. Currency PCA model

For currencies, the PCA analysis leads to the model of Lustig, Roussanov, and Verdelhan (2011). Consistent with their work, we report in Panel A of Table 12 that the first two principal components account for 87% of the time series variation of the interest rate-sorted currency portfolios. The loadings of the first principal component reveal that it can be interpreted as a level factor because it loads on the returns of all currency portfolios similarly. Analogously, the loadings of the second principal component reveal that it can be interpreted as a slope factor because it loads on the differential return when going from Portfolio 1 to Portfolio 6A. Intuitively, these two principal components can be approximated by two portfolios: an equally weighted portfolio of all currencies in the sample against the dollar and a carry trade portfolio created by a long position in Portfolio 6A and a short position in Portfolio 1. We refer to these two portfolios as the dollar and carry portfolios, and we denote their returns by RX_{cur} and HML_{cur}, respectively. To confirm the intuition, Table 13 reports in the top left panel that the correlation between the first principal component and the dollar portfolio is 100% and the correlation between the second principal component and the carry portfolio is 95%.

Table 14 presents the estimates of both the PCA-based linear model of Lustig, Roussanov, and Verdelhan (2011) and the DR-CAPM on the cross section of currency returns. The LRV model explains 64% of the cross-sectional variation in currency returns. The estimated price of risk is statistically significant for the carry portfolio but not for

[24] This robustness check also minimizes concerns about the reliability of second-stage Fama and MacBeth standard errors due to the presence of estimated regressors.

Table 8
Betas of first-stage time series regressions: capital asset pricing model (CAPM) beta-sorted, industry, and equity index option portfolios.

The table reports first-stage time series unconditional and downstate betas with ordinary least squares (OLS) standard errors in parentheses for portfolios of equity and equity index options excess returns. Panel A reports these statistics for five beta-sorted equity portfolios and a betting against beta factor (BAB). Panel B reports the statistics for the five Fama and French industry portfolios. Panels C and D report the statistics for nine put and call option portfolios on the Standard & Poor's 500 with maturities between 30 and 90 days and moneyness between 90 and 110, respectively. The sample period is January 1974 to March 2010 for a total of 435 observations in Panels A and B, and April 1986 to March 2010 for a total of 288 observations in Panels C and D.

	β	SE_{OLS}	β^-	SE_{OLS}
Panel A : CAPM beta – sorted equity portfolios				
Portfolio				
Low	0.69	(0.03)	0.99	(0.10)
2	0.93	(0.03)	1.18	(0.11)
3	1.04	(0.03)	1.25	(0.10)
4	1.20	(0.03)	1.26	(0.11)
High	1.46	(0.05)	1.34	(0.13)
BAB	−0.05	(0.04)	0.48	(0.15)
Panel B : Fama and French industry portfolios				
Consumer, portfolio 1	0.90	(0.02)	1.01	(0.10)
Manufacturing, portfolio 2	0.85	(0.02)	0.90	(0.09)
High technology, portfolio 3	1.15	(0.03)	0.92	(0.14)
Health, portfolio 4	0.82	(0.04)	0.81	(0.15)
Other, portfolio 5	1.04	(0.02)	1.12	(0.10)
Panel C : Equity index put option portfolios				
Expiration 30, moneyness 90, portfolio 1	1.10	(0.05)	1.54	(0.24)
Expiration 30, moneyness 100, portfolio 2	0.98	(0.03)	1.01	(0.13)
Expiration 30, moneyness 110, portfolio 3	0.89	(0.02)	0.75	(0.08)
Expiration 60, moneyness 90, portfolio 4	1.08	(0.04)	1.50	(0.18)
Expiration 60, moneyness 100, portfolio 5	0.98	(0.03)	1.00	(0.12)
Expiration 60, moneyness 110, portfolio 6	0.91	(0.02)	0.79	(0.08)
Expiration 90, moneyness 90, portfolio 7	1.06	(0.04)	1.44	(0.16)
Expiration 90, moneyness 100, portfolio 8	0.98	(0.03)	1.00	(0.12)
Expiration 90, moneyness 110, portfolio 9	0.91	(0.02)	0.81	(0.09)
Panel D : Equity index call option portfolios				
Expiration 30, moneyness 90, portfolio 1	0.82	(0.02)	0.43	(0.08)
Expiration 30, moneyness 100, portfolio 2	0.74	(0.03)	0.28	(0.11)
Expiration 30, moneyness 110, portfolio 3	0.48	(0.04)	0.07	(0.16)
Expiration 60, moneyness 90, portfolio 4	0.81	(0.02)	0.42	(0.08)
Expiration 60, moneyness 100, portfolio 5	0.76	(0.03)	0.30	(0.11)
Expiration 60, moneyness 110, portfolio 6	0.59	(0.04)	0.20	(0.14)
Expiration 90, moneyness 90, portfolio 7	0.80	(0.02)	0.42	(0.07)
Expiration 90, moneyness 100, portfolio 8	0.76	(0.03)	0.30	(0.10)
Expiration 90, moneyness 110, portfolio 9	0.66	(0.03)	0.20	(0.14)

the dollar portfolio. The model is statistically rejected by the χ^2 test on the pricing errors with a p-value of 0%. The slope factor, the carry portfolio, carries most of the information relevant for the cross section. A model that includes only the first principal component, the level factor or dollar portfolio, generates a R^2 of only 4%. Similar to the DR-CAPM, the largest individual pricing error for the LRV model (−0.2%) is for the low-yield currency portfolio (Portfolio 1).

The DR-CAPM captures the information contained in the principal components that is relevant for this cross section. Intuitively, the DR-CAPM summarizes the two principal components because the unconditional market return acts as a level factor while downside risk acts as a slope factor. To confirm this intuition, recall from Table 10, Panel A, that the unconditional market betas are relatively similar across currency portfolios, so that all portfolios load similarly on the market. In contrast, the downside betas are more strongly increasing going from Portfolio 1 to Portfolio 6, thus providing a slope factor. The top two panels in Table 13 confirm that the second principal component (or the carry portfolio) is more highly correlated with the market portfolio in downstates (28% correlation), thus loading on downside risk, than it is unconditionally (9% correlation). The DR-CAPM produces a R^2 of 73% and RMSPE of 0.10 that are similar to the R^2 of 64% and RMSPE of 0.12 of the LRV model.

6.2. Equity PCA model

The PCA on the cross section of equities provided by the six Fama and French portfolios sorted on size and book-to-market leads to the three-factor model of Fama and French (1992). Panel B in Table 12 shows that the first three principal components account for 98% of the time series variation of the size and book-to-market-sorted portfolios. The loadings of the first principal component reveal that it can be interpreted as a level factor because it loads on the returns of all equity portfolios similarly. The loadings of the second and third principal components reveal that

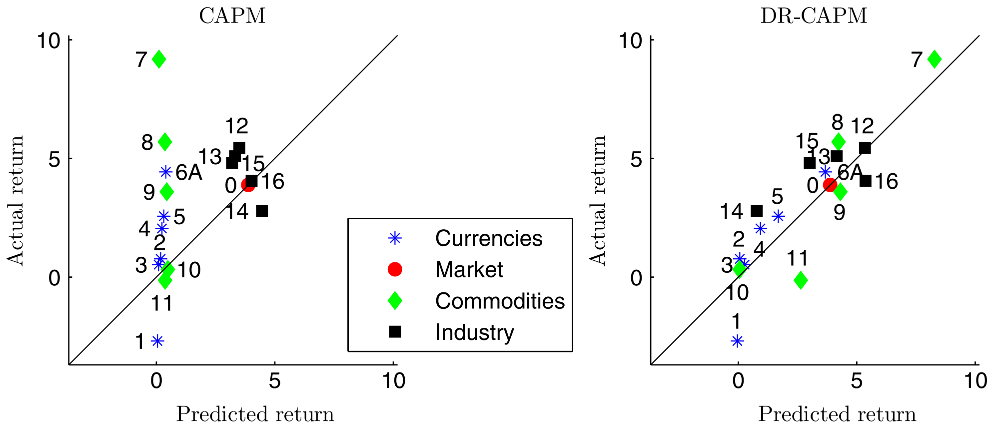

Fig. 11. Model performance: currencies, commodities, and industry portfolios.
Depicted are annualized mean excess returns versus the predicted excess returns in percent for the unconditional capital asset pricing model (CAPM) in the left panel and the downside risk CAPM (DR-CAPM) in the right panel. Test assets are six currency portfolios (1 to 6A), monthly re-sampled based on the interest rate differential with the US, five commodity futures portfolios monthly re-sampled based on basis (7 to 11) as well as the five Fama and French industry portfolios (12 to 16). The market excess return is included as a test asset (0). High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. The sample period is January 1974 to December 2008 for a total of 420 observations.

they can be interpreted as two slope factors. The second principal component mainly loads on the differential return when going from small portfolios (1 to 3) to big portfolios (4 to 6). The third principal component mainly loads on the differential return when going from growth portfolios (1 and 4) to value portfolios (3 and 6). However, the interpretation is not as clear as it is for currencies (or for commodities). For example, the third principal component does not affect Portfolios 2 and 5 in a way consistent with its interpretation as a factor affecting the value-growth trade-off in returns.

We approximate the first principal component with the market return and the next two principal components by the Fama and French factors: the small-minus-big portfolio and the high-minus-low portfolio. We denote the returns of these two portfolios as SMB and HML_{ff}, respectively. Table 13 shows in the middle left panel that the first principal component is highly correlated with the market (95% correlation), the second principal component is mainly related to the SMB return (80% correlation), and the third principal component is mainly related to the HML_{ff} return (82% correlation). However, HML_{ff} and SMB returns are themselves correlated and, therefore, do not correspond exactly to the two principal components that are by construction orthogonal to each other. Correspondingly, we find that HML_{ff} is also correlated with the second principal component and SMB is correlated with the third principal component.[25]

Table 15 presents the estimates of both the PCA-based linear model of Fama and French (1992) and the DR-CAPM on the cross section of equity returns. The Fama and French three-factor model explains 68% of the cross-sectional variation in returns. The estimated prices of risk are significant for the market and HML_{ff} but not for SMB. The model is statistically rejected by the χ^2 test on the joint pricing errors with a p-value of 0%. The cross-sectional performance of the model is driven by the third principal component, which is approximated by the HML_{ff} factor. A model based only on the first two principal components generates a R^2 of -4%.

The DR-CAPM is unable to match the small-growth equity returns of Portfolio 1 (pricing error of -0.45%) and, therefore, produces a lower R^2 (33%) than the Fama and French three-factor model. As noted by Campbell and Vuolteenaho (2004), it is typical in the literature to find that models cannot correctly price Portfolio 1 and a number of papers (Lamont and Thaler, 2003; D'Avolio, 2002; Mitchell, Pulvino, and Stafford, 2002) question whether its return is correctly measured.[26] In the last column of Table 15 we show that once we remove Portfolio 1 from the six Fama and French portfolios, the DR-CAPM performance improves. The R^2 increases to 90% and the hypothesis of zero joint pricing errors cannot be rejected by the χ^2 test at the 5% confidence level.

[25] The correlation between HML_{ff} and SMB helps to rationalize why the interpretation of the equity principal components in terms of mimicking portfolios is not as clear as it is for currencies or commodities. In the case of currencies and, as is shortly illustrated, in the case of commodities, the proxy portfolios of the two principal components are themselves almost uncorrelated. For example, the correlation between RX_{cur} and HML_{cur} is only 0.07.

[26] These papers refer to Portfolio 1 as the small-growth portfolio in the 25-portfolio sorting of Fama and French, while our first portfolio is the small-growth portfolio in the six-portfolio sorting of Fama and French. Our first portfolio, therefore, includes more securities than those considered troublesome in the cited papers. In the online Appendix, however, we verify that the DR-CAPM mispricing of the first portfolio in our setting is due to the securities that are part of the smallest growth portfolios in the 25-portfolio sorting. Our results, therefore, are consistent with the previous evidence on small-growth stocks.

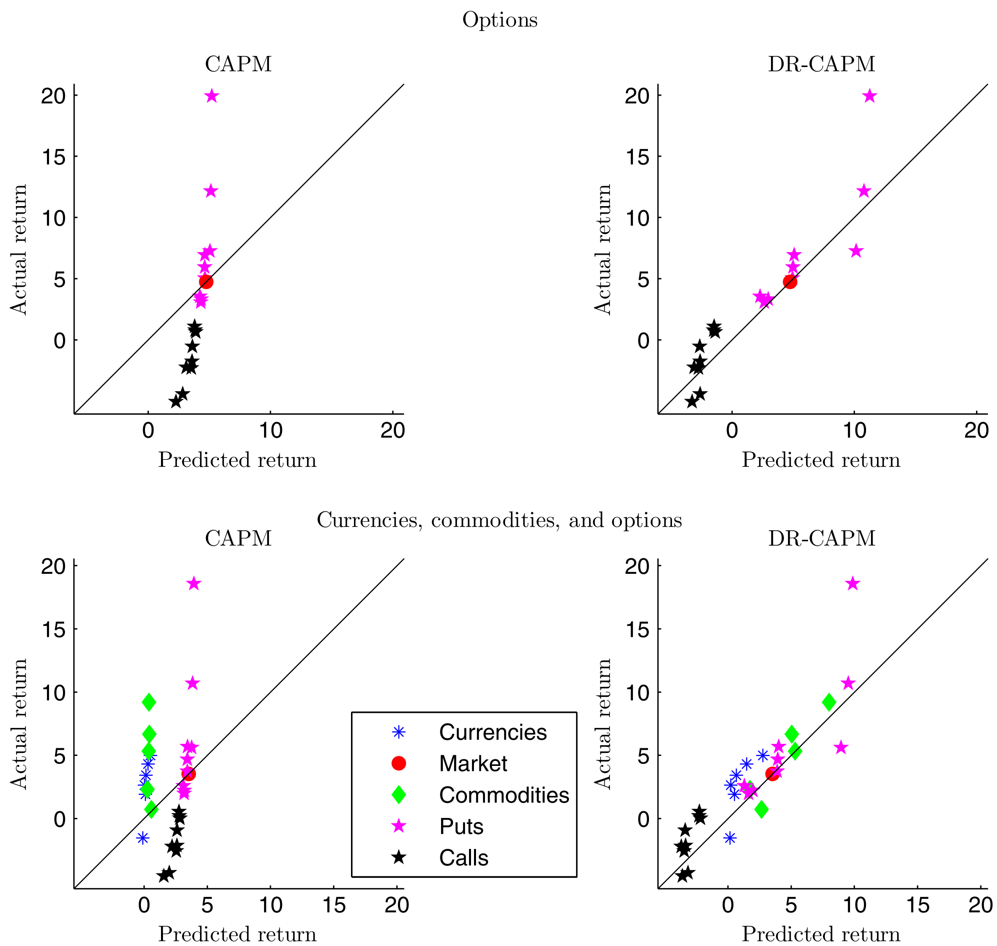

Fig. 12. Model performance: currencies, commodities, and equity index options.
Depicted are annualized mean excess returns versus the predicted excess returns in percent for the unconditional capital asset pricing model (CAPM) in the left panels and the downside risk CAPM (DR-CAPM) in the right panels for six currency portfolios, monthly re-sampled based on the interest rate differential with the US, five commodity futures portfolios monthly re-sampled based on basis as well as 18 portfolios of call and put options on the Standard & Poor's 500 with maturities between 30 and 90 days and moneyness between 90 and 110. The market excess return is included as a test asset. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has an annualized monthly inflation of 10% higher than US inflation. The sample period is April 1986 and to March 2010 for a total of 288 observations and to December 2008 for a total of 273 observations when the commodity portfolios are included.

6.3. *Commodity PCA model*

The PCA on the cross section of commodities leads to the model of Yang (2013). Consistent with his work, we report in Panel C of Table 12 that the first two principal components account for 75% of the time series variation of the basis-sorted commodity portfolios. The loadings of the first principal component reveal that it can be interpreted as a level factor because it loads on the returns of all commodity portfolios similarly. Analogously, the loadings of the second principal component reveal that it can be interpreted as a slope factor because it loads on the differential return when going from Portfolio 1 to Portfolio 5. Intuitively, these two principal components can be approximated by two portfolios: an equally weighted portfolio of all commodities contained in the sample and a basis trade portfolio created by a long position in Portfolio 1 and a short position in Portfolio 5. We refer to these two portfolios as the commodity and basis portfolios and denote their returns by RX_{com} and HML_{com}, respectively. To confirm this intuition, the bottom left panel of Table 13 shows that the correlation between the first principal component and the commodity portfolio is 100% and the correlation between the second principal component and the basis portfolio is 95%.

Table 16 presents the estimates of both the PCA-based linear model of Yang (2013) and the DR-CAPM on the cross section of currency returns. The Yang model explains 87% of the cross-sectional variation in expected returns. The estimated price of risk is statistically significant for both the commodity and basis portfolios. The hypothesis of zero joint pricing errors cannot be rejected by the χ^2 test with a p-value of 50%. The slope factor, the basis portfolio, carries most of the information relevant for the cross section. A model that includes only the first principal component,

Table 9
Estimation of linear pricing models: currencies, commodities, and equity index options.
This table reports prices of risk, Fama and MacBeth standard errors in parentheses, χ^2 statistics testing for joint significance of pricing errors, root mean squared pricing errors (RMSPE), the number of observations T and the cross sectional R^2's for the unconditional capital asset pricing model (CAPM) and the downside risk CAPM (DR-CAPM). In Columns 1 and 2, test assets are 18 portfolios of call and put options on the Standard & Poor's 500 with maturities between 30 and 90 days and moneyness between 90 and 110. Columns 3 and 4 add six currency portfolios, monthly re-sampled based on the interest rate differential with the US and five commodity futures portfolios monthly re-sampled based on basis. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. The sample period is April 1986 and to March 2010 for a total of 288 observations and to December 2008 for a total of 273 observations when the commodity portfolios are included. Starred estimates impose the restriction that the market excess-return is exactly priced and consequently no standard errors are reported.

	Options		Currencies, commodities, and options	
	CAPM (1)	DR-CAPM (2)	CAPM (3)	DR-CAPM (4)
λ	0.40*	0.40*	0.29*	0.29*
λ^-		1.14		1.13
		(0.27)		(0.27)
χ^2	162.72	162.63	211.95	211.89
P-value	0.00%	0.00%	0.00%	0.00%
RMSPE	0.44	0.21	0.39	0.20
R^2	18.90%	81.43%	−1.89%	74.45%
T	288	288	273	273

the level factor or commodity portfolio, generates a R^2 of only 10%.

The DR-CAPM captures the information contained in the principal components that is relevant for this cross section. Intuitively, the DR-CAPM summarizes the two principal components because the unconditional market return acts as a level factor, while downside risk acts as a slope factor. To confirm this intuition, recall from Table 10, Panel C, that the unconditional market betas are similar across commodity portfolios, so that all portfolios load similarly on the market, while the downside betas are decreasing when going from Portfolio 1 to Portfolio 5, thus providing a slope factor.[27] The bottom two panels in Table 13 confirm that the basis portfolio (or the second principal component) is more highly correlated with the market portfolio in down states (19% correlation), thus loading on downside risk, than it is unconditionally (−5% correlation). The DR-CAPM produces a R^2 of 82% and RMSPE of 0.12 that are similar to the R^2 of 87% and RMSPE of 0.10 of the Yang model. The hypothesis that the DR-CAPM pricing errors are jointly zero cannot be rejected by the χ^2 test with a p-value of 66%.

Having investigated the factor structure of each asset class separately, we conclude that for each asset class the DR-CAPM has similar explanatory power to the PCA model that is specifically designed for that asset class. We emphasize that the underlying reason is that in each asset class the factor structure is composed of level and slope factors that the DR-CAPM picks up with the market and downside risk factors, respectively.

[27] For commodity portfolios the unconditional betas are almost increasing when going from Portfolio 1 to Portfolio 5, but the effect is quantitatively small and dominated by the more strongly decreasing downside betas.

6.4. PCA models across asset classes

We now turn to investigate the factor structure of the joint cross section of currencies, equities, and commodities. Fig. 14 plots together the loadings of the principal component analysis performed on each asset class separately. The left panel suggests that the first principal component in each asset class represents a joint level factor. The right panel shows that the subsequent principal components of each asset class are common slope components.

Tables 17 and 18 explore the predictive power of the PCA-based models analyzed above and the DR-CAPM across asset classes. Table 17 estimates the models using the proxy portfolios, and Table 18 employs directly the principal components. Each of the asset class-specific models is unable to price the joint cross section. Both the LRV model and the Yang model have negative R^2 (−15% and −35%, respectively), and the Fama and French model has a modest R^2 of 35%. The LRV model estimates a significant price of risk for the carry portfolio, and the estimate increases to 0.99 from the 0.47 estimate obtained when using only currency portfolios as test assets. The price of risk of the dollar portfolio remains statistically insignificant. The Yang model estimates a significant price of risk for the commodity portfolio but not for the basis portfolio. The Fama and French model estimates a significant price of risk only for the HML_{ff} portfolio. The point estimates for the prices of risk of the market, SMB, and HML_{ff} portfolios are 0.28, 0.23, and 0.57, respectively. These point estimates are overall comparable to the 0.36, 0.19, and 0.49 estimates obtained when using only the equity portfolios as test assets. The failure of asset class-specific models to price other asset classes has induced a search for segmented theoretical models that could explain why different stochastic discount factors are needed to price different asset classes. We view our DR-CAPM

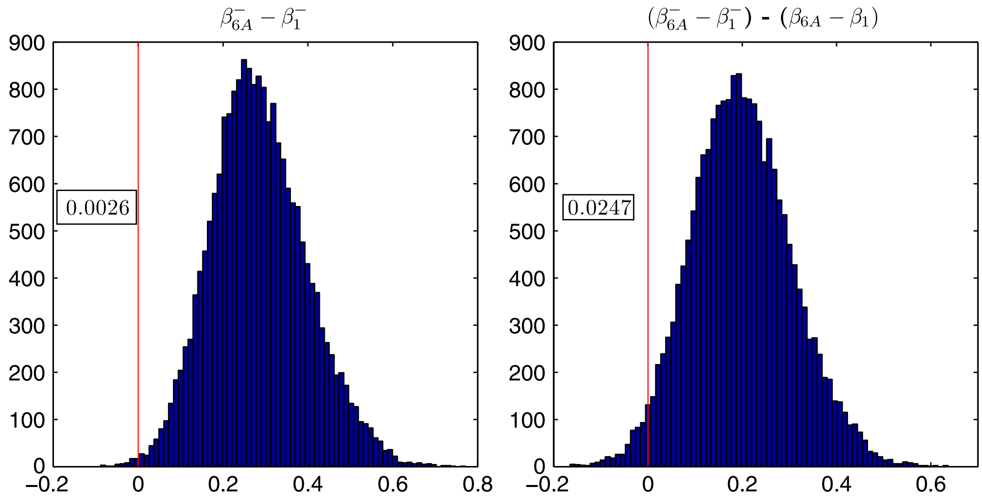

Fig. 13. Bootstrapped distribution: currencies relative downstate betas.
Depicted are bootstrapped distributions of the difference in downstate betas of the last and first currency portfolios, $\beta^-_{6A} - \beta^-_1$, in the left panel and the difference in downstate minus unconditional betas of the last and first currency portfolios, $(\beta^-_{6A} - \beta^-_1) - (\beta_{6A} - \beta_1)$, in the right panel. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has an annualized monthly inflation of 10% higher than US inflation. We employ a smoothed bootstrap scheme consisting of re-sampling empirical residuals and adding zero centered normally distributed noise using twenty thousand iterations.

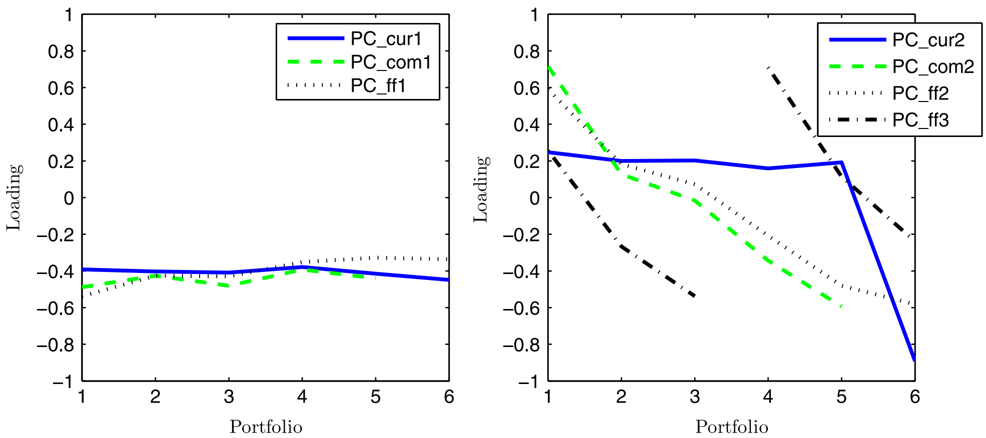

Fig. 14. Principal component analysis (PCA) loadings: currencies, equities, and commodities.
Depicted are loadings of the principal component analysis for six currency portfolios, monthly re-sampled based on the interest rate differential with the US, five commodity futures portfolios monthly re-sampled based on basis as well as the six Fama and French portfolios sorted on size and book-to-market. The PCA is performed separately on the portfolios of each asset class. The left panel plots the loadings of the first principal components of each asset class: PC_cur1, PC_ff1, and PC_com1 for currencies, equities, and commodities, respectively. The right panel plots the loadings of the second principal component for currencies (PC_cur2), the second principal component for commodities (PC_com2), and the second and third principal components for equities (PC_ff2, PC_ff3). High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has an annualized monthly inflation of 10% higher than the US. The sample period is January 1974 to March 2010 for a total of 435 observations for currencies and equities and to December 2008 for a total of 420 observations for the commodity portfolios.

results as suggesting that a unified view of risk markets is still possible.

To obtain an explanatory power similar to the DR-CAPM, the PCA analysis suggests using between four and eight principal components.[28] A naive approach that simply adds principal components leads to using the first eight principal components. The first two columns in Table 18 show that the resulting model must be discarded as many of the estimated prices of risk are not statistically significant.

A better model can be built using the information gleaned from the factor structure of each asset class. Since most of the explanatory power for the cross section of each asset class comes from a slope factor, it is intuitive to suggest a model that includes only the slope factors of each asset class and a common level factor. The third and second to last columns in Tables 17 and 18 show that a model that uses the first and third principal components of the equity portfolios,

[28] We refer here to the principal components obtained by performing the PCA on the joint returns of currencies, equities, and commodities. Details of this PCA are reported in the online Appendix.

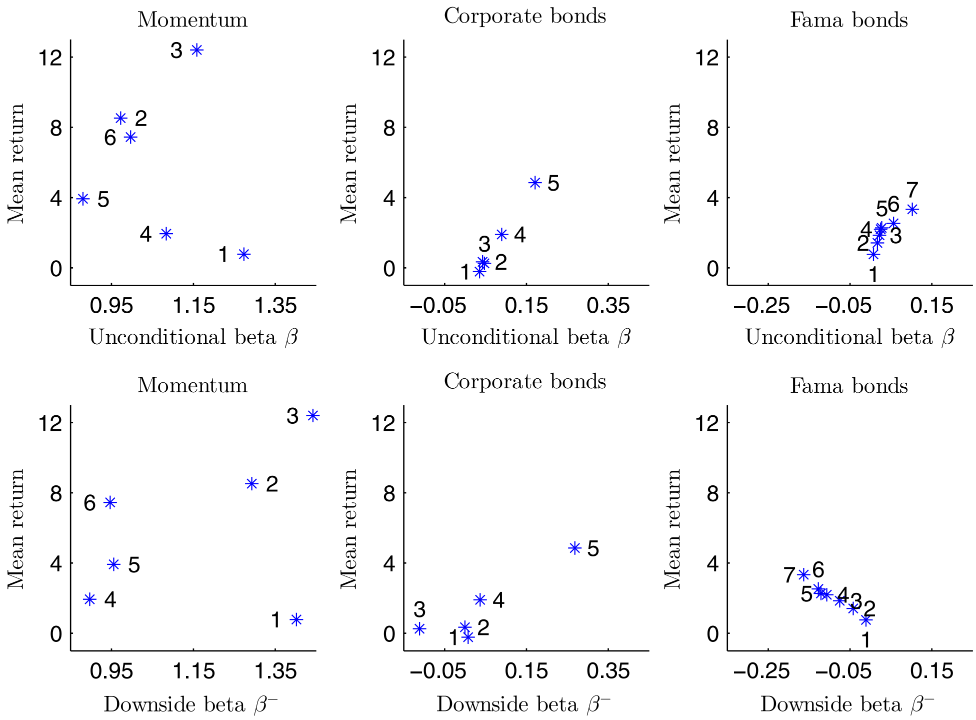

Fig. 15. Risk–return relations: Equity momentum, corporate bonds, and T-bills.
Depicted are risk–return relations for the six Fama and French portfolios sorted on size and momentum (left panels), five corporate bond portfolios annually re-sampled based on their credit spread by Nozawa (2012) (middle panels), and seven zero coupon US Treasury bonds (right panels). The top panels plot the realized mean excess return versus the capital asset pricing model beta (β), while the bottom panels plot the downside betas (β^-). The sample period is January 1974 to March 2010 for a total of 435 observations for the equity portfolios, October 1975 to March 2010 for a total of 414 observations for the commodity portfolios, and January 1974 to March 2010 for a total of 183 observations for the US Treasury bond portfolios.

Table 10
Betas of first-stage time series regressions: currencies, equities, and commodities.
This table reports first-stage time series unconditional and downstate betas with ordinary least squares (OLS) standard errors in parentheses for portfolios of currency, equity, and commodity (excess) returns. Panel A reports these statistics for six currency portfolios, monthly re-sampled based on the interest rate differential with the US. Panel B reports the statistics for the six Fama and French portfolios sorted on size and book-to-market. Panel C reports the statistics for five commodity futures portfolios monthly re-sampled based on the commodity basis. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. The sample period is January 1974 to March 2010 for a total of 435 observations in Panel A and B and January 1974 to December 2008 for a total of 420 observations in Panel C.

	β	SE_{OLS}	β^-	SE_{OLS}
Panel A : Six currency portfolios				
Interest rate differential				
Low	0.03	(0.02)	0.02	(0.10)
2	0.06	(0.02)	0.04	(0.10)
3	0.04	(0.02)	0.04	(0.09)
4	0.08	(0.02)	0.10	(0.08)
5	0.10	(0.02)	0.17	(0.10)
High	0.10	(0.03)	0.18	(0.10)
6A	0.11	(0.03)	0.30	(0.13)
Panel B : Six Fama and French portfolios				
Small size				
Low book-to-market, portfolio 1	1.31	(0.03)	1.47	(0.11)
Medium book-to-market, portfolio 2	1.01	(0.03)	1.28	(0.12)
High book-to-market, portfolio 3	1.00	(0.03)	1.34	(0.14)
Big size				
Low book-to-market, portfolio 4	1.01	(0.01)	0.90	(0.05)
Medium book-to-market, portfolio 5	0.89	(0.02)	0.92	(0.08)
High book-to-market, portfolio 6	0.87	(0.02)	0.96	(0.13)
Panel C : Commodity futures portfolios				
Basis				
Low	0.03	(0.06)	0.53	(0.26)
2	0.09	(0.05)	0.33	(0.23)
3	0.11	(0.05)	0.35	(0.25)
4	0.13	(0.05)	0.10	(0.20)
High	0.10	(0.05)	0.23	(0.25)

Table 11
Model robustness.

This table reports prices of risk, Fama and MacBeth standard errors in parentheses, root mean squared pricing errors (RMSPE), the number of observations T and the cross sectional R^2's for the downside risk capital asset pricing model (DR-CAPM). Test assets are six currency portfolios, monthly re-sampled based on the interest rate differential with the US, and the six Fama and French portfolios, sorted on size and book-to-market where indicated. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. In Columns 1 and 2, market prices of risk are estimated based only on the six Fama and French portfolios and the market excess return. The reported standard errors correspond to this estimation. The estimated prices of risk are then used to fit the six currency portfolios or the six currency portfolios and the Fama and French portfolios jointly. Columns 3 and 4 vary the downstate cutoff. Downstate in the low (high) threshold specification are all months in which the market returns is more than 1.5 (0.5) standard deviations below its sample mean. Columns 5 and 6 vary the inflation cutoff. A country is considered to have high inflation if is has annualized monthly inflation 5% (15%) higher than US inflation. The market excess-return is included as a test asset. The sample period is January 1974 to March 2010 for a total of 435 observations. Starred estimates impose the restriction that the market excess-return is exactly priced and consequently no standard errors are reported.

	Equity prices of risk		Low downstate threshold	High downstate threshold	5% inflation threshold	15% inflation threshold
	Currencies (1)	Currencies and equities (2)	Currencies (3)	Currencies (4)	Currencies (5)	Currencies (6)
λ	0.39*	0.39*	0.39*	0.39*	0.39*	0.39*
λ^-	1.27	1.27	1.95	2.72	2.55	2.13
	(0.45)	(0.45)	(0.49)	(0.84)	(0.94)	(0.60)
χ^2			23.38	16.27	23.94	25.21
P-value			0.07%	1.24%	0.05%	0.03%
RMSPE	0.12	0.16	0.15	0.09	0.09	0.09
R^2	66.62%	70.99%	47.16%	77.76%	80.20%	80.99%
T	435	435	435	435	435	435

Table 12
Principal component analysis: currencies, equities, and commodities.

The table reports loadings [PC1–PC3] and percentage of the total variance explained by each principal component of a principal components analysis on the covariance matrix of: in Panel A, six currencies portfolios (Cur-PF1 to Cur-PF6A), monthly re-sampled based on the interest rate differential with the US. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. In Panel B, the six Fama and French portfolios (FF-PF1 to FF-PF6), sorted on size and book-to-market. In Panel C, five commodity futures portfolios (Com-PF1 to Com-PF5), monthly re-sampled based on basis. The sample period is January 1974 to March 2010 in Panels A and B for a total of 435 observations, and January 1974 to December 2008 in Panel C for a total of 420 observations.

	PC1	PC2	PC3
Panel A. PCA currency portfolios			
Cur-PF1	−0.39	0.25	0.55
Cur-PF2	−0.40	0.20	0.37
Cur-PF3	−0.41	0.20	−0.05
Cur-PF4	−0.38	0.16	−0.15
Cur-PF5	−0.41	0.19	−0.73
Cur-PF6A	−0.45	−0.89	0.04
Explained	68.78%	17.76%	5.03%
Panel B : PCA Fama and French portfolios			
FF-PF1	−0.54	0.59	0.26
FF-PF2	−0.43	0.18	−0.27
FF-PF3	−0.43	0.07	−0.54
FF-PF4	−0.35	−0.21	0.71
FF-PF5	−0.33	−0.48	0.11
FF-PF6	−0.34	−0.58	−0.24
Explained	86.37%	6.98%	4.73%
Panel C : PCA commodity portfolios			
Com-PF1	−0.49	0.72	0.41
Com-PF2	−0.43	0.13	−0.46
Com-PF3	−0.48	−0.02	−0.28
Com-PF4	−0.39	−0.34	−0.38
Com-PF5	−0.44	−0.59	0.63
Explained	59.99%	15.08%	10.45%

Table 13
Correlations: currencies, equities, and commodities.

The top panels contain correlations between market excess return (Mrkt), dollar and carry currency portfolio returns (RX_{cur} and HML_{cur}) and the first two principal components of six currency portfolios sorted on the interest differential ($PC_{cur\ 1}$ and $PC_{cur\ 2}$), monthly re-sampled based on the interest rate differential with the US. High inflation countries in the last currency portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. The middle panels contain the three Fama and French factor returns (Mrkt, SMB and HML_{ff}) and the first three principal components of the six Fama and French portfolios sorted on size and book-to-market ($PC_{ff\ 1}$, $PC_{ff\ 2}$, and $PC_{ff\ 3}$). The bottom panels contain the market excess return (Mrkt), commodity and basis portfolio returns (RX_{com} and HML_{com}), and the first two principal components of five commodity futures portfolios sorted on basis ($PC_{com\ 1}$ and $PC_{com\ 2}$). The left-hand columns report unconditional correlations, and the right-hand columns condition on the downstate. Downstates are all months in which the market return is more than 1 standard deviation below its sample mean. The sample period is January 1974 to March 2010 for a total of 435 observations in the top and middle panels and January 1974 to December 2008 for a total of 420 observations in the bottom panels.

	All states					Down states				
	Mrkt	RX_{cur}	HML_{cur}	$PC_{cur\ 1}$	$PC_{cur\ 2}$	Mrkt	RX_{cur}	HML_{cur}	$PC_{cur\ 1}$	$PC_{cur\ 2}$
Mrkt	1.00	0.17	0.14	−0.17	−0.09	1.00	0.17	0.33	−0.17	−0.28
RX_{cur}	0.17	1.00	0.07	−1.00	0.02	0.17	1.00	0.13	−1.00	−0.06
HML_{cur}	0.14	0.07	1.00	−0.09	−0.95	0.33	0.13	1.00	−0.15	−0.97
$PC_{cur\ 1}$	−0.17	−1.00	−0.09	1.00	0.00	−0.17	−1.00	−0.15	1.00	0.08
$PC_{cur\ 2}$	−0.09	0.02	−0.95	0.00	1.00	−0.28	−0.06	−0.97	0.08	1.00

	All states						Down states					
	Mrkt	SMB	HML_{ff}	$PC_{ff\ 1}$	$PC_{ff\ 2}$	$PC_{ff\ 3}$	Mrkt	SMB	HML_{ff}	$PC_{ff\ 1}$	$PC_{ff\ 2}$	$PC_{ff\ 3}$
Mrkt	1.00	0.25	−0.33	−0.95	−0.15	0.23	1.00	0.45	0.00	−0.91	0.01	−0.16
SMB	0.25	1.00	−0.23	−0.48	0.80	−0.36	0.45	1.00	0.02	−0.64	0.66	−0.44
HML_{ff}	−0.33	−0.23	1.00	0.24	−0.51	−0.82	0.00	0.02	1.00	−0.27	−0.66	−0.90
$PC_{ff\ 1}$	−0.95	−0.48	0.24	1.00	0.00	0.00	−0.91	−0.64	−0.27	1.00	−0.02	0.49
$PC_{ff\ 2}$	−0.15	0.80	−0.51	0.00	1.00	0.00	0.01	0.66	−0.66	−0.02	1.00	0.30
$PC_{ff\ 3}$	0.23	−0.36	−0.82	0.00	0.00	1.00	−0.16	−0.44	−0.90	0.49	0.30	1.00

	All states					Down states				
	Mrkt	RX_{com}	HML_{com}	$PC_{com\ 1}$	$PC_{com\ 2}$	Mrkt	RX_{com}	HML_{com}	$PC_{com\ 1}$	$PC_{com\ 2}$
Mrkt	1.00	0.11	−0.05	−0.11	−0.08	1.00	0.20	0.19	−0.20	0.21
RX_{com}	0.11	1.00	0.05	−1.00	−0.02	0.20	1.00	0.07	−1.00	0.04
HML_{com}	−0.05	0.05	1.00	−0.07	0.95	0.19	0.07	1.00	−0.09	0.95
$PC_{com\ 1}$	−0.11	−1.00	−0.07	1.00	0.00	−0.20	−1.00	−0.09	1.00	−0.05
$PC_{com\ 2}$	−0.08	−0.02	0.95	0.00	1.00	0.21	0.04	0.95	−0.05	1.00

Table 14
Estimation of linear pricing models: currencies.

The table reports prices of risk, Fama and MacBeth standard errors in parentheses, χ^2 statistics testing for joint significance of pricing errors, root mean squared pricing errors (RMSPE), the number of observations T and the cross sectional R^2's for various factor models, and the downside risk capital asset pricing model (DR-CAPM). Columns 1 and 2 present models based on the first two principal components of the test assets (PC1 and PC2). Column 3 presents the dollar and carry portfolio returns of Lustig and Verdelhan (2007) (RX_{cur} and HML_{cur}). Column 4 presents the DR-CAPM. Test assets are six currency portfolios, monthly re-sampled based on the interest rate differential with the US. High inflation countries in the last portfolio are excluded. A country is considered to have high inflation if it has annualized monthly inflation 10% higher than US inflation. The sample period is January 1974 to March 2010 for a total of 435 observations. A starred estimate imposes the restriction that the market excess return is exactly priced and consequently no standard errors are reported.

	PC1 (1)	PC2 (2)	LRV (3)	DR-CAPM (4)
PC1	−0.33	−0.33		
	(0.23)	(0.23)		
PC2		−0.32		
		(0.12)		
RX_{cur}			0.13	
			(0.09)	
HML_{cur}			0.47	
			(0.15)	
λ_{market}				0.39*
λ_{-}				2.18
				(0.77)
χ^2	43.24	36.05	25.14	24.60
P-value	0.00%	0.00%	0.00%	0.02%
RMSPE	0.19	0.14	0.12	0.10
R^2	4.47%	50.07%	63.71%	73.04%
T	435	435	435	435

Table 15
Estimation of linear pricing models: equities.

The table reports prices of risk, Fama and MacBeth standard errors in parentheses, χ^2 statistics testing for joint significance of pricing errors, root mean squared pricing errors (RMSPE), the number of observations T and the cross sectional R^2's for various factor models and the downside risk capital asset pricing model (DR-CAPM). Columns 1 and 2 present models based on the first three principal components of the test assets (PC1, PC2, and PC3). Column 3 presents a model based on the three Fama and French factors (Mrkt, SMB, and HML_{ff}). Column 4 presents the DR-CAPM. Test assets are the six Fama and French portfolios sorted on size and book-to-market. Column 5 excludes the small growth portfolio. The sample period is January 1974 to March 2010 for a total of 435 observations. Starred estimates impose the restriction that the market excess return is exactly priced and consequently no standard errors are reported.

	PC2 (1)	PC3 (2)	Fama and French (3)	DR-CAPM (4)	DR-CAPM excluding portfolio 1 (5)
PC1	−1.37	−1.37			
	(0.60)	(0.60)			
PC2	−0.25	−0.25			
	(0.17)	(0.17)			
PC3		−0.51			
		(0.14)			
Mrkt			0.36		
			(0.23)		
SMB			0.19		
			(0.15)		
HML_{ff}			0.49		
			(0.15)		
λ_{market}				0.39*	0.39*
λ_{-}				1.27	1.61
				(0.45)	(0.43)
χ^2	55.58	42.15	41.77	33.83	9.43
P-value	0.00%	0.00%	0.00%	0.00%	5.12%
RMSPE	0.25	0.14	0.14	0.20	0.07
R^2	−3.57%	67.25%	68.27%	32.93%	90.48%
T	435	435	435	435	435

the second principal component of the currency portfolios, and the second principal component of the commodity portfolios or, alternatively, their mimicking portfolios (i.e., the market, HML_{ff}, carry, and basis portfolios) performs similarly to the DR-CAPM. The estimated prices of risk are statistically significant for all slope components, or for their mimicking portfolios, but not for the level component or market return. This PCA-based model generates a R^2 of 59% and RMSPE of 0.19 when using the principal components and a R^2 of 70% and RMSPE of 0.16 when using the mimicking portfolios. The DR-CAPM performs similarly with a R^2 of 74% and RMSPE of 0.15 and is once again able to jointly summarize the information contained in all of these principal components in just two factors.

6.5. Other factor structures and further research

While the DR-CAPM is able to price returns in many important asset classes, it is not universally successful. In this subsection we present results for asset classes for which the DR-CAPM is not successful: momentum portfolios, corporate bonds, and US Treasuries. Instead of estimating the full model, we plot the relation of the downside risk beta with average returns in the bottom panels of Fig. 15, while the top panels show the relation of average returns with the standard CAPM beta.

The left panels of Fig. 15 show results for equity portfolios sorted on momentum.[29] While the returns of these portfolios appear to be unrelated to beta, they are broadly positively associated with downside beta with the exception of the first momentum portfolio, which consists of small firms with very low recent returns. However, the association with downside beta is not sufficiently strong for the DR-CAPM to fully capture the returns of the momentum portfolios.

[29] We use six US equity portfolios sorted on size and momentum by Fama and French and available on Ken French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The sample period is from January 1974 to March 2010.

Table 16
Estimation of linear pricing models: commodities.

The table reports prices of risk, Fama and MacBeth standard errors in parentheses, χ^2 statistics testing for joint significance of pricing errors, root mean squared pricing errors (RMSPE), the number of observations T and the cross sectional R^2's for various factor models and the downside risk capital asset pricing model (DR-CAPM). Columns 1 and 2 present models based on the first two principal components of the test assets (PC1 and PC2). Column 3 presents the model based on the commodity and basis portfolio returns of Yang (2013) (RX_{com} and HML_{com}). Column 4 presents the DR-CAPM. Test assets are five commodity futures portfolios, monthly re-sampled based on basis. The sample period is January 1974 to December 2008 for a total of 420 observations. A starred estimate imposes the restriction that the market excess return is exactly priced and consequently no standard errors are reported.

	PC1 (1)	PC2 (2)	Yang (2013) (3)	DR-CAPM (4)
PC1	−0.73	−0.73		
	(0.41)	(0.41)		
PC2		0.60		
		(0.20)		
PC3				
RX_{com}			0.31	
			(0.18)	
HML_{com}			0.83	
			(0.28)	
λ_{market}				0.32*
λ_{-}				1.42
				(0.57)
χ^2	9.33	0.68	2.37	2.42
P-value	5.34%	87.84%	49.90%	65.98%
RMSPE	0.27	0.05	0.10	0.12
R^2	10.41%	96.83%	87.14%	81.61%
T	420	420	420	420

Table 17
Estimation of linear pricing models: currencies, equities, and commodities (mimicking portfolios).

This table reports prices of risk, Fama and MacBeth standard errors in parentheses, χ^2 statistics testing for joint significance of pricing errors, root mean squared pricing errors (RMSPE), the number of observations T and the cross sectional R^2's for various factor models and the downside risk capital asset pricing model (DR-CAPM). Column 1 presents the model based on the dollar and carry portfolio returns of Lustig and Verdelhan (2007) (RX_{cur} and HML_{cur}). Column 2 presents the model based on the commodity and basis portfolio returns of Yang (2013) (RX_{com} and HML_{com}). Column 3 presents a model based on the three Fama and French factors (Mrkt, SMB and HML_{ff}). Columns 4 and 5 present models based on combinations of the portfolio returns in columns 1 to 3. Test assets are six currency portfolios, monthly re-sampled based on the interest rate differential with the US, the six Fama and French portfolios sorted on size and book-to-market and five commodity futures portfolios, monthly re-sampled based on basis. The sample period is January 1974 to December 2008 for a total of 420 observations. A starred estimate imposes the restriction that the market excess return is exactly priced and consequently no standard errors are reported.

	Cur_{mim} (1)	Com_{mim} (2)	FF_{mim} (3)	Cur_{mim} Com_mim FF_{mim} (4)	Cur_{mim} Com_{mim} FF_{mim} (5)	DR-CAPM (6)
RX_{cur}	0.19			0.10		
	(0.11)			(0.10)		
HML_{cur}	0.99			0.42	0.50	
	(0.37)			(0.15)	(0.16)	
RX_{com}		0.43		0.31		
		(0.19)		(0.18)		
HML_{com}		0.54		0.83	0.91	
		(0.31)		(0.28)	(0.29)	
Mrkt			0.28	0.31	0.40	
			(0.23)	(0.23)	(0.24)	
SMB			0.23	0.18		
			(0.16)	(0.16)		
HML_{ff}			0.57	0.49	0.49	
			(0.18)	(0.15)	(0.17)	
λ_{market}						0.32*
λ_{-}						1.40
						(0.38)
χ^2	113.18	120.09	107.48	84.30	87.49	64.48
P-value	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
RMSPE	0.32	0.34	0.24	0.12	0.16	0.15
R^2	−14.96%	−35.22%	35.29%	82.37%	69.50%	73.52%
T	420	420	420	420	420	420

The middle panel shows results for US corporate bonds.[30] While the CAPM beta and the downside beta are both positively associated with these portfolio returns, the spread in average returns is too small compared with the spread in downside betas.

The right panels in Fig. 15 show that the DR-CAPM performs worst on returns of US Treasuries of various maturities.[31] While bond returns are positively associated with their unconditional beta, they are negatively related to their downside beta. Cochrane and Piazzesi (2005) show that the cross section of average bond returns is, in fact, driven by a single factor that is not strongly associated with market returns. Fig. 15 shows that the bond factor is also not driven by downside market risk.

Finally, we stress once more that our purpose was not to test a specific theoretical framework in the data but to show a novel pattern, the exposure to downside risk, across many asset classes. Consequently, the model presented in Section 2 should not be regarded as a formal asset pricing model, but as an approximate reduced-form model for asset returns that is convenient to highlight the novel risk exposure in the data. We are

[30] We use the monthly returns on the five corporate bond portfolios sorted annually on their credit spread by Nozawa (2012). The sample period is from October 1975 to March 2010. Portfolio 1 is composed of the lowest credit spread bonds, and Portfolio 5 is composed of the highest credit spread bonds. The five portfolios are obtained by equally weighting the ten portfolios in the benchmark analysis of Nozawa (2012) into five baskets.

[31] We use the monthly bond returns in the Fama bond file of CRSP. The sample period is from January 1974 to March 2010. Portfolios 1 to 5 are formed with bonds with maturities less than or equal to one to five years, respectively. Portfolio 6 is formed with bonds with maturities less or equal than ten years and Portfolio 7 with bonds with maturities greater than ten years.

Table 18

Estimation of linear pricing models: currencies, equities, and commodities.

The table reports prices of risk, Fama and MacBeth standard errors in parentheses, χ^2 statistics testing for joint significance of pricing errors, root mean squared pricing errors (RMSPE), the number of observations T and the cross sectional R^2's for various factor models and the downside risk capital asset pricing model (DR-CAPM). Columns 1 and 2 present models based on the first eight principal components of the test assets (PC1 to PC8). Column 3 presents a model based on the first two principal components of the currency portfolios ($PC_{cur\ 1}$ and $PC_{cur\ 2}$). Column 4 presents a model based on the first two principal components of the commodity portfolios ($PC_{com\ 1}$ and $PC_{com\ 2}$). Column 5 presents a model based on the first three principal components of the stock portfolios ($PC_{ff\ 1}$ to $PC_{ff\ 3}$). Columns 6 and 7 present models based on combinations of the principal components in columns 3 to 5. Test assets are six currency portfolios, monthly re-sampled based on the interest rate differential with the US, the six Fama and French portfolios sorted on size and book-to-market and five commodity futures portfolios, monthly re-sampled based on basis. The sample period is January 1974 to December 2008 for a total of 420 observations. A starred estimate imposes the restriction that the market excess return is exactly priced and consequently no standard errors are reported.

	PC7 (1)	PC8 (2)	PC_{cur} (3)	PC_{com} (4)	PC_{ff} (5)	PC_{cur} PC_{com} PC_{ff} (6)	PC_{cur} PC_{com} PC_{ff} (7)	DR-CAPM (8)
$PC1/PC_{cur\ 1}$	−1.32	−1.32	−0.55			−0.27		
	(0.60)	(0.60)	(0.28)			(0.24)		
$PC2/PC_{cur\ 2}$	0.55	0.55	−0.73			−0.28	−0.29	
	(0.40)	(0.40)	(0.27)			(0.12)	(0.12)	
$PC3/PC_{com\ 1}$	0.08	0.08		−0.97		−0.72		
	(0.23)	(0.23)		(0.42)		(0.41)		
$PC4/PC_{com\ 2}$	−0.57	−0.57		0.35		0.60	0.59	
	(0.20)	(0.20)		(0.23)		(0.20)	(0.20)	
$PC5/PC_{ff\ 1}$	−0.24	−0.24			−1.26	−1.22	−1.26	
	(0.18)	(0.18)			(0.60)	(0.60)	(0.60)	
$PC6/PC_{ff\ 2}$	0.22	0.22			−0.21	−0.25		
	(0.16)	(0.16)			(0.17)	(0.17)		
$PC7/PC_{ff\ 3}$	0.10	0.10			−0.63	−0.52	−0.58	
	(0.15)	(0.15)			(0.18)	(0.14)	(0.18)	
PC8		−0.60						
		(0.14)						
λ_{market}								0.32*
λ_{-}								1.40
								(0.38)
χ^2	111.56	93.14	123.01	118.39	107.72	91.80	97.69	64.48
P-value	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
RMSPE	0.19	0.12	0.33	0.34	0.24	0.12	0.19	0.15
R^2	59.08%	83.03%	−28.62%	−35.32%	36.07%	83.62%	59.48%	73.52%
T	420	420	420	420	420	420	420	420

aware that the return data-generating process, by the nature of its approximate form, misprices some assets whose payoffs are connected with the threshold property. Similarly, we have been intentionally silent on the deeper foundations of downside risk. It remains an open question for future research to derive models capable of matching the strong empirical patterns highlighted in this paper as well as providing a structural interpretation to the risk factors.

7. Conclusion

We find that currency returns are associated with aggregate market risk, thus supporting a risk-based view of exchange rates. However, we find that the unconditional CAPM cannot explain the cross section of currency returns because the spread in currency betas is not sufficiently large to match the cross-sectional variation in expected returns. The downside risk CAPM (DR-CAPM) explains currency returns because the difference in beta between high- and low-yield currencies is higher conditional on bad market returns, when the market price of risk is also high, than it is unconditionally.

We also find that the DR-CAPM can jointly explain the cross section of currencies, equity, equity index options, commodities, and sovereign bond returns. We view these results as not only confirming the empirical performance of the model but also as a first step in reconciling discount factors across asset classes. The performance of the model across asset classes contrasts with the failure of models designed for a specific asset class in pricing other asset classes.

Our results open new avenues for future research. Given its demonstrated empirical relevance, it is important to gain a deeper theoretical understanding of the sources and time variation of downside risk. It remains an open question whether downside risk comes from preferences or from micro-founded constraints.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jfineco.2014.07.001.

References

Adrian, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross section of asset returns. Journal of Finance, http://dx.doi.org/10.1111/jofi.12189, in press.

Ang, A., Chen, J., Xing, Y., 2006. Downside risk. Review of Financial Studies 19, 1191–1239.

Asness, C., Moskowitz, T., Pedersen, L.H., 2013. Value and momentum everywhere. Journal of Finance 68, 929–985.

Bansal, R., Dahlquist, M., 2000. The forward premium puzzle: different tales from developed and emerging economies. Journal of International Economics 51, 115–144.

Barro, R.J., 2006. Rare disasters and asset markets in the twentieth century. Quarterly Journal of Economics 121, 823–866.

Borri, N., Verdelhan, A., 2011. Sovereign risk premia. Unpublished working paper. Massachusetts Institute of Technology, Cambridge, MA.

Brunnermeier, M.K., Nagel, S., Pedersen, L.H., 2008. Carry trades and currency crashes. NBER Macroeconomics Annual, pp. 313–348.

Burnside, C., 2011a. Carry trades and risk. NBER Working Paper 17278. National Bureau of Economic Research.

Burnside, C., 2011b. The cross section of foreign currency risk premia and consumption growth risk: comment. American Economic Review 101, 3456–3476.

Burnside, C., Eichenbaum, M., Kleshchelski, I., Rebelo, S., 2011. Do peso problems explain the returns to the carry trade? Review of Financial Studies 24, 853–891.

Burnside, C., Eichenbaum, M., Rebelo, S., 2009. Understanding the forward premium puzzle: a microstructure approach. American Economic Journal: Macroeconomics 1, 127–154.

Burnside, C., Eichenbaum, M., Rebelo, S., 2011. Carry trade and momentum in currency markets. Annual Review of Financial Economics 3, 511–535.

Burnside, C., Han, B., Hirshleifer, D., Wang, T.Y., 2011. Investor overconfidence and the forward premium puzzle. The Review of Economic Studies 78, 523–558.

Caballero, R.J., Doyle, J.B., 2012. Carry trade and systemic risk: Why are fx options so cheap? Working Paper 18644. National Bureau of Economic Research.

Campbell, J., Vuolteenaho, T., 2004. Bad beta, good beta. American Economic Review 94, 1249–1275.

Christiansen, C., Ranaldo, A., Soederlind, P., 2011. The time-varying systematic risk of carry trade strategies. Journal of Financial and Quantitative Analysis 46, 1107–1125.

Cochrane, J.H., 2005. Asset Pricing, revised ed. Princeton University Press, Princeton, NJ.

Cochrane, J.H., 2011. Presidential address: discount rates. Journal of Finance 66, 1047–1108.

Cochrane, J.H., Piazzesi, M., 2005. Bond risk premia. American Economic Review 95, 138–160.

Constantinides, G.M., Jackwerth, J.C., Savov, A., 2013. The puzzle of index option returns. Review of Asset Pricing Studies 3, 229–257.

D'Avolio, G., 2002. The market for borrowing stock. Journal of Financial Economics 66, 271–306.

Dobrynskaya, V., 2014. Downside market risk of carry trades. Review of Finance, http://dx.doi.org/10.1093/rof/rfu004, in press.

Fama, E., French, K., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fama, E., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.

Farhi, E., Fraiberger, S.P., Gabaix, X., Ranciere, R., Verdelhan, A., 2012. Crash risk in currency markets. Unpublished working paper. Harvard University, New York University, International Monetary Fund, and Massachusetts Institute of Technology, Cambridge, MA, New York, NY, and Washington, DC.

Farhi, E., Gabaix, X., 2008. Rare disasters and exchange rates. NBER Working Papers 13805. National Bureau of Economic Research.

Frazzini, A., Pedersen, L.H., 2014. Betting against beta. Journal of Financial Economics 111, 1–25.

Gorton, G.B., Hayashi, F., Rouwenhorst, K.G., 2013. The fundamentals of commodity futures returns. Review of Finance 17, 35–105.

Gul, F., 1991. A theory of disappointment aversion. Econometrica 59, 667–686.

Harvey, C.R., Siddique, A., 2000. Conditional skewness in asset pricing tests. Journal of Finance 55, 1263–1295.

Jurek, J., 2014. Crash-neutral currency carry trades. Journal of Financial Economics, http://dx.doi.org/10.1016/j.jfineco.2014.05.004, in press.

Koijen, R.S., Moskowitz, T.J., Pedersen, L.H., Vrugt, E.B., 2013. Carry. Working Paper 19325. National Bureau of Economic Research.

Lamont, O., Thaler, R., 2003. Can the market add and subtract? Mispricing in the tech stock carve-puts. Journal of Political Economy 111, 227–268.

Leland, H.E., 1999. Beyond mean–variance: performance measurement in a nonsymmetrical world. Financial Analysts Journal 55, 27–36.

Lustig, H., Roussanov, N., Verdelhan, A., 2011. Common risk factors in currency markets. Review of Financial Studies 24, 3731–3777.

Lustig, H., Verdelhan, A., 2007. The cross section of foreign currency risk premia and consumption growth risk. American Economic Review 97, 89–117.

Lustig, H., Verdelhan, A., 2011. The cross section of foreign currency risk premia and consumption growth risk: reply. American Economic Review 101, 3477–3500.

Markowitz, H., 1959. Portfolio Selection: Efficient Diversification of Investments. Wiley and Sons, New York, NY. Reprinted 1970, Yale University Press, New Haven, CT; second ed., 1991, Basil Blackwell, Oxford, UK.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012. Carry trades and global foreign exchange volatility. The Journal of Finance 67, 681–718.

Mitchell, M., Pulvino, T., Stafford, E., 2002. Limited arbitrage in equity markets. Journal of Finance 57, 551–584.

Mueller, P., Stathopoulos, A., Vedolin, A., 2012. International correlation risk. Unpublished working paper. London School of Economics and University of Southern California, London, UK, and Los Angeles, CA.

Nozawa, Y., 2012. Corporate bond premia. Unpublished working paper. University of Chicago, Chicago, IL.

Routledge, B., Zin, S., 2010. Generalized disappointment aversion and asset prices. Journal of Finance 65, 1303–1332.

Shanken, J., 1992. On the estimation of beta-pricing models. Review of Financial Studies 5, 1–55.

Yang, F., 2013. Investment shocks and the commodity basis spread. Journal of Financial Economics 110, 164–184.