Currency Carry, Momentum, and Global Interest Rate Volatility

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A. Internet Appendix

A. Model Solution and Proof of Propositions

Following Gabaix and Maggiori (2015), the optimal demand at t is

$$Q_t = \frac{1}{\Gamma_t} E_t[\frac{R_t^*}{R_t} e_{t+1} - e_t].$$

The market clearing conditions at each date are

$$e_0 - \iota_0 - Q_0 = 0,$$

$$e_1 - \iota_1 + RQ_0 - Q_1 = 0,$$

$$e_2 - \iota_2 + RQ_1 - Q_2 = 0,$$

$$e_3 - \iota_3 + R_2 Q_2 = 0.$$

I solve the model backward. Plugging market clearing condition at $t = 2$ and 3 into the optimal demand at $t = 2$ gives

$$Q_2 = \frac{1}{\Gamma_2} E_2(\frac{R_2^*}{R_2}(\iota_3 - R_2 Q_2) - (\iota_2 + Q_2 - RQ_1)).$$

The optimal demand Q_2 then can be solved out

$$Q_2 = \frac{R_2^*/R_2 - 1}{1 + \Gamma_2 + R_2^*} \iota_2 + \frac{R}{1 + \Gamma_2 + R_2^*} Q_1 = q_{21}\iota_2 + q_{22} Q_1, \tag{IA.1}$$

where to ease notation I have defined two coefficients q_{21} and q_{22}. The equilibrium exchange rate at $t = 2$ is then

$$e_2 = (1 + q_{21})\iota_2 + (q_{22} - R)Q_1. \tag{IA.2}$$

Via the same method, we can solve out

$$Q_1 = \frac{R^*/R(1 + E_1 q_{21}) - 1}{1 + \Gamma_1 + R^* - R^*/RE_1 q_{22}}\iota_1 + \frac{R}{1 + \Gamma_1 + R^* - R^*/RE_1 q_{22}}Q_0 = q_{11}\iota_1 + q_{12}Q_0, \tag{IA.3}$$

$$Q_0 = \frac{R^*/R(1 + E_0 q_{11}) - 1}{1 + \Gamma_0 + R^* - R^*/RE_0 q_{12}}\iota_0 = q_{01}\iota_0. \tag{IA.4}$$

1. Proof of Proposition 1

Financier's effective risk-aversion at $t = 1$

$$\Gamma_1 = \gamma(Var_1(e_2))^\alpha = \gamma(Var_1[g(R_2^*, R_2, \iota_2)])^\alpha \tag{IA.5}$$

with non-linear function $g(\cdot)$ given by Eq. (IA.2). Note that at $t = 1$, Γ_2, R, Q_1 are known parameters.[1] Since R_2^*, R_2, ι_2 follow conditional normal distribution at $t = 1$, the conditional variance of the non-linear function $g(\cdot)$ can be calculated via the delta method:

$$Var_1[g(R_2^*, R_2, \iota_2)] = \nabla g(R_2^*, R_2, \iota_2 | R^*, R, \iota_1)' \begin{pmatrix} \sigma_G^2 + \sigma_r^{*2} & \sigma_G^2 & 0 \\ \sigma_G^2 & \sigma_G^2 + \sigma_r^2 & 0 \\ 0 & 0 & \sigma_\iota^2 \end{pmatrix} \nabla g(R_2^*, R_2, \iota_2 | R^*, R, \iota_1).$$

[1] $\Gamma_2 = \gamma Var_2(e_3)^\alpha = \gamma\sigma_\iota^2$.

The Jacobian of function $g(\cdot)$ is evaluated at the conditional mean of R_2^*, R_2, ι_2, which is R^*, R, ι_1. Expressing the Jacobian as

$$\nabla g(R_2^*, R_2, \iota_2) = \begin{pmatrix} g_{R^*} \\ g_R \\ g_\iota \end{pmatrix},$$

then

$$\Gamma_1 = \gamma[(g_{R^*} + g_R)^2 \sigma_G^2 + g_{R^*}^2 \sigma_r^{*2} + g_R^2 \sigma_r^2 + g_\iota^2 \sigma_\iota^2]^\alpha.$$

Hence Γ_1 increases with σ_G.

2. Proof of Proposition 2

Since $\Gamma_2 > 0$ and $R_2^* > 1$, we must have $q_{22} < R$ and hence $E_0 q_{22} < R$. As interest rate are constant at $t = 0$ and $t = 1$, and time-1 news from ι_1 is unrelated to R_2^*, then we have

$$E_1 q_{22} = E_0 q_{22} < R.$$

Similarly from the assumption $E_0 \frac{R_2^*/R_2 - 1}{1 + \Gamma_2 + R_2^*} = E_0 q_{21} > 0$, we have $E_1 q_{21} = E_0 q_{21} > 0$. Therefore, when $R^* > R$, q_{11} is a positive-valued random variable

$$q_{11} = \frac{R^*/R(1 + E_1 q_{21}) - 1}{1 + \Gamma_1 + R^* - R^*/R E_1 q_{22}} > 0,$$

which will imply $E_0 q_{11} > 0$. Meanwhile we have

$$q_{12} = \frac{R}{1 + \Gamma_1 + R^* - R^*/RE_1 q_{22}} < R,$$

so that $E_0 q_{12} < R$. Thus from Equation (IA.4) we obtain $q_{01} > 0$ and $Q_0 > 0$.

Finally, from the market clearing condition at $t = 1$, we have

$$\frac{\partial e_1}{\partial \Gamma_1} = \frac{\partial Q_1}{\partial \Gamma_1} = \frac{\partial (q_{11}\iota_1 + q_{12}Q_0)}{\partial \Gamma_1} < 0.$$

This is because $\frac{\partial q_{11}}{\partial \Gamma_1} < 0$ and $\frac{\partial q_{12}}{\partial \Gamma_1} < 0$. Combing with Proposition 1, we obtain

$$\frac{\partial e_1}{\partial \sigma_G^2} = \frac{\partial e_1}{\partial \Gamma_1}\frac{\partial \Gamma_1}{\partial \sigma_G^2} < 0.$$

3. Proof of Proposition 3

In the setup with extended period, first note that the financier still starts to trade at $t = 0$. Thus the market clearing condition at $t = -1$ is $e_{-1} = \iota_{-1}$.

The optimal demand at $t = 1$ and 2 can still be written following (IA.1) and (IA.3)

$$Q_2 = q_{21}\iota_2 + q_{22}Q_1$$

$$Q_1 = q_{11}\iota_1 + q_{12}Q_0.$$

Note that the new condition $E_0 q_{21} = 0$ implies $E_1 q_{21} = 0$ and hence $q_{11} = 0$, so

$$Q_1 = q_{12} Q_0.$$

When $R^* = R$, financiers' optimal demand at $t = 0$ is

$$Q_0 = \frac{1}{\Gamma_0} E_0(e_1 - e_0) = \frac{1}{\Gamma_0} E_0(\iota_1 + Q_1 - RQ_0 - e_0).$$

Since their expectation at $t = 0$ is

$$E_0 \iota_1 = \delta \iota_1 + (1 - \delta)\iota_0,$$

I thus have

$$E_0(\iota_1 + Q_1) = \delta \iota_1 + (1 - \delta)\iota_0 + Q_0 E_0 q_{12}.$$

Replacing the market clearing condition at $t = 0$ and $t = 1$ into the optimal demand at $t = 0$

$$Q_0 = \frac{1}{\Gamma_0} E_0(\iota_1 + Q_1 - RQ_0 - e_0) = \frac{1}{\Gamma_0} E_0(\iota_1 + Q_1 - RQ_0 - \iota_0 - Q_0),$$

which can be written as

$$Q_0 = \frac{\delta(\iota_1 - \iota_0)}{\Gamma_0 + R + 1 - E_0 q_{12}}. \tag{IA.6}$$

The realized currency appreciation between time -1 and 0 is then

$$e_0 - e_{-1} = Q_0 + \iota_0 - \iota_{-1} = \iota_0 - \iota_{-1} + \frac{\delta(\iota_1 - \iota_0)}{\Gamma_0 + R + 1 - E_0 q_{12}}, \tag{IA.7}$$

and that between 0 and 1 is

$$e_1 - e_0 = \iota_1 - \iota_0 + Q_1 - (R+1)Q_0 = \iota_1 - \iota_0 + (q_{12} - R - 1)Q_0 = [1 + \frac{(q_{12} - R - 1)\delta}{\Gamma_0 + R + 1 - E_0 q_{12}}](\iota_1 - \iota_0).$$

Because ι_t follows the random walk (15), the currency momentum effect is manifested by the covariance (conditional on ι_{-1})

$$Cov(e_1 - e_0, e_0 - e_{-1}) = \frac{\delta}{\Gamma_0 + R + 1 - E_0 q_{12}}[1 + \frac{(q_{12} - R - 1)\delta}{\Gamma_0 + R + 1 - E_0 q_{12}}]\sigma_\iota^2.$$

Since $q_{12} < R$ and $E_0 q_{12} < R$, when the underreaction is strong enough such that $\delta < \bar{\delta}$, the currency momentum effect exists so that

$$Cov(e_2 - e_1, e_1 - e_0) > 0.$$

The cutoff level can be computed as

$$\bar{\delta} = \min\{\frac{\Gamma_0 + R + 1 - E_0 q_{12}}{R + 1 - q_{12}}, 1\}. \tag{IA.8}$$

To prove (ii), the covariance between equilibrium financiers' holding Q_0 and realized appreciation

$e_0 - e_{-1}$ can be calculated from (IA.6) and (IA.7):

$$Cov(Q_0, e_0 - e_{-1}) = (\frac{\delta}{\Gamma_0 + R + 1 - E_0 q_{12}})^2 \sigma_l^2 > 0.$$

And from the market clearing conditions at $t = -1$ and $t = 0$, $Q_0 > 0$ if and only if foreign currency appreciates sufficiently so that $e_0 - e_{-1} > \iota_0 - \iota_{-1}$.

Finally, if the global IRV increases unexpectedly at $t = 1$,

$$\frac{\partial e_1}{\partial \sigma_G^2} = \frac{\partial e_1}{\partial \Gamma_1}\frac{\partial \Gamma_1}{\partial \sigma_G^2} = \frac{\partial \Gamma_1}{\partial \sigma_G^2}\frac{\partial Q_1}{\partial \Gamma_1} = \frac{\partial \Gamma_1}{\partial \sigma_G^2}\frac{\partial q_{12}}{\partial \Gamma_1}Q_0,$$

with $\frac{\partial q_{12}}{\partial \Gamma_1} = -\frac{R}{(1+\Gamma_1+R^*-R^*/RE_1 q_{12})^2} < 0$ and $\frac{\partial \Gamma_1}{\partial \sigma_G^2} > 0$. Thus we obtain $\frac{\partial e_1}{\partial \sigma_G^2} < 0$.

B. Data Appendix and Computation Details

1. Data source

The full dataset of currencies covers 48 countries from January 1985 to January 2019, within which the classification of developed economies includes 21 countries: Australia, Austria, Belgium, Canada, Denmark, Euro, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The 27 developing economies cover Brazil, Bulgaria, Croatia, Cyprus, Czech Republic, Egypt, Hong Kong, Hungary, Iceland, India, Indonesia, Israel, Kuwait, Malaysia, Mexico, Philippines, Poland, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Taiwan, Thailand, and Ukraine. The series for the euro start from January 1999 and I exclude the Eurozone currencies after that date. Due to the large failures of covered interest rate parity, the following observations are removed from the sample: South Africa from July 1985 to August 1985, Malaysia from August 1998 to June 2005, Indonesia from December 2000 to May 2007. The final dates of all G10 daily bond data are as of January 2019, but the starting months vary over countries and are listed in the following table.

Currency	Starting month
AUD	November 1999
CAD	July 1989
CHF	March 2007
DEM/EUR	August 1990
GBP	January 1992
JPY	April 1989
NOK	March 2007
NZD	November 1999
SEK	January 2007
USD	January 1985

Other data include the daily FX returns, which are used to obtain global FX volatility and correlation following Menkhoff et al. (2012a) and Mueller et al. (2017a). Detailed sample periods for alternative risk factors used in the asset pricing test are:

Factor	Sample period
TED	Jan 1986 to Jan 2019
Bond liquidity	Dec 1985 to Mar 2017
Betting against beta	Jan 1985 to Jan 2019
Intermediary's equity capital ratio	Jan 1985 to Nov 2018
FX bid-ask spread	Jan 1985 to Jan 2019
VIX	Jan 1986 to Jan 2019
Global FX volatility	Jan 1985 to Jan 2019
Economic Policy Uncertainty	Jan 1985 to Jan 2019
Global FX correlation	Jan 1985 to Jan 2019
Downside risk	Jan 1985 to Jan 2019
US consumption growth	Jan 1985 to Jan 2019
Global Imbalance	Jan 1985 to Dec 2012
HML_{carry}	Jan 1985 to Jan 2019
HML_{mom}	Jan 1985 to Jan 2019

2. Adjustment for transaction costs, calculation of idiosyncratic volatility and skewness

Following Menkhoff et al. (2012b) and many others, at the end of month $t+1$, and for currency i, if it leaves the sorted portfolio that is formed at month t after $t+1$, then the *net* excess return for the lowest portfolio (the portfolio being shorted) is computed as

$$rx^{s}_{t+1} = f^{a}_{t} - s^{b}_{t+1}, \tag{IA.9}$$

where the superscripts a and b represent the ask and bid prices. For the long portfolios above the bottom one, the net excess returns are

$$rx^l_{t+1} = f^b_t - s^a_{t+1}. \tag{IA.10}$$

On the other hand, if currency i does not leave the current portfolio, then the excess returns are computed as

$$rx^s_{t+1} = f^a_t - s_{t+1}, \quad rx^l_{t+1} = f^b_t - s_{t+1}. \tag{IA.11}$$

To compute two measures of the limits to arbitrage for each currency i, I follow Filippou et al. (2018) by first extracting the residual series from the following asset pricing model

$$rx^i_t = \alpha^i + \beta^i_1 DOL_t + \beta_2 HML_{carry,t} + \epsilon_{i,t}, \tag{IA.12}$$

where DOL_t and $HML_{carry,t}$ are the daily dollar factor and the slope factor from carry trade portfolios. This asset pricing model is proposed by Lustig et al. (2011), and the regression is estimated by using daily data within each month. Then the currency i's idiosyncratic volatility and skewness at month-T are computed as

$$IV_{i,T} = \sqrt{\frac{\sum_{j=1}^{N_T} \hat{\epsilon}^2_{i,d}}{N_T}}, \quad IS_{i,T} = \frac{\sum_{j=1}^{N_T} \hat{\epsilon}^3_{i,d}}{N_T (IV_{i,T})^3}, \tag{IA.13}$$

where N_T denotes the number of daily returns available during month-T.

3. Extracting risk factor from the BBD MPU index

The US Monetary Policy Uncertainty (MPU) index built by Baker et al. (2016) is constructed as the scaled frequency counts of articles that discuss US monetary policy uncertainty, from hundreds of US daily newspapers covered by Access World News. To obtain their shocks as the risk factor, I follow Della Corte and Krecetovs (2019) by first computing the simple change in MPU level:

$$\Delta MPU_t = MPU_t - MPU_{t-1}. \tag{IA.14}$$

However, ΔMPU_t is highly correlated with changes in other category-specific BBD policy uncertainty indexes,[2] which confound the identification of shocks. I thus run the following orthogonalization:

$$\Delta MPU_t = \alpha + \sum_j \beta_j \Delta EPU_{j,t} + u_t^{MPU}, \tag{IA.15}$$

where $EPU_{j,t}$ denotes the BBD policy uncertainty index of category-j, and u_t^{MPU} denotes the orthogonal MPU shocks used in the paper. For variables on the right-hand side of Equation (IA.15), I consider four categories that cover Taxes; Fiscal and government spending; Sovereign debt; and National security. The selection follows their relevance for FX markets and results are not sensitive to other choices.

[2]In addition to the uncertainty over monetary policy, Baker et al. (2016) also builds the policy uncertainty indexes for the categories such as the fiscal policy, sovereign debt, etc.

C. Stock and Bond Flow-based Evidence for the Impact of IRV

I provide flow-based evidence for the US bond and equity markets to support the proposed channel in Section A. I test whether the capital inflows to the US are positively associated with foreign currency appreciation against the USD, and whether shocks to the global IRV indeed dampen the inflows. I use monthly data of country-level cross-border equity and bond transactions against the US, available from the Treasury International Capital (TIC) system. The sample overlaps 43 countries with my currency sample.[3] I define the net inflow to the US from country i, $InFlow_t^i$, as the net purchases of US stocks and bonds by foreign residents minus the net purchases of country i's stocks and bonds by US residents. Since asset flows may grow over time and their sizes vary across countries, for valid comparison I follow Hau and Rey (2004) by dividing $InFlow_t^i$ by the total volume of equity and bond transactions between country i and the US.

I test whether foreign currency appreciations positively predict inflows to the US. At the end of each month t I sort all 43 countries into four portfolios based on past 3-month appreciations against the USD,[4] then I calculate the average inflows to the US for each portfolio. The left hand side of Panel A in Table A1 lists the results, where the first row reports the average inflows to the US for the current month and the following rows report the results for the subsequent three

[3] The missing five economies are Croatia, Euro, Iceland, Slovakia and Slovenia. As explained in Bertaut and Judson (2014), the TIC data are filed with district Federal Reserve Banks by commercial banks, securities dealers, other financial institutions, and nonbanking enterprises in the US. Reporting is legally required if their monthly transactions are above \$50 million during the reporting month. This data has been widely used in the international finance literature to link capital flows with exchange rates (see e.g, Hau and Rey, 2004).

[4] I form four instead of five portfolios since the number of currencies becomes smaller.

months . Consistent with my argument above, foreign currency appreciations positively predict contemporaneous and subsequent inflows to the US. The cross-sectional relation is close to monotonic and with positive and significant high-minus-low differences. The predictability can also be tested by estimating the following regressions using the Fama-MacBeth procedures

$$\text{(IA.16)} \qquad InFlow^i_{t+j} = b_0 + b \times (-\Delta s^i_{t-3:t}) + \epsilon^i_{t+j},$$

$$\text{(IA.17)} \qquad InFlow^i_{t+j} = b_0 + b_{rank} \times rank(-\Delta s^i_{t-3:t}) + \epsilon^i_{t+j}, \qquad i = 1, 2, \cdots N_t,$$

with N_t the number of countries with available data at month-t and $-\Delta s^i_{t-3:t}$ is the past 3-month appreciation of currency i against the USD. I consider the second specification where I use the cross-sectional ranking of currency appreciations as the regressor, given the relatively small size of cross-section and potential impact of outlier. The right-hand side of Panel A reports the regression results, which resemble those from the portfolio sorting. Currency appreciations on average predict higher net inflows to the US, and the results are even stronger if using cross-sectional ranking as the predictor. These results suggest that past appreciated currencies indeed create excess supply for FX intermediaries to absorb and thus have higher expected returns.

Furthermore, to show that the risk of global IRV adversely affects the inflows, I augment (IA.17) by adding an interaction term with shocks to the global IRV:

(IA.18)

$$InFlow^i_t = \alpha + (\beta_0 + \beta_1 u^{IRV}_t) \times rank(-\Delta s^i_{t-3:t}) + \gamma_1 InFlow^i_{t-1} + \gamma_2 InFlow^i_{t-2} + \gamma_3 InFlow^i_{t-3} + \epsilon^i_t,$$

TABLE A1

Momentum, asset flows, and impact of IRV

The table reports the results of using past 3-month currency appreciations against the USD to predict contemporaneous and subsequent net inflows to the US, $InFlow^i_{t+j}$. The net inflows are calculated as the net purchases of US stocks and bonds by foreign residents minus the net purchases of country i's stocks and bonds by US residents, scaled by the total volume of equity and bond transactions between country i and the US. The left part of Panel A reports the average inflows for each of the portfolios formed by sorting on the past 3-month appreciations against the USD. The right part of Panel A reports the parameter estimates and their t-statistics from the Fama-MacBeth regressions (IA.16) and (IA.17). Panel B reports the results from Fama-MacBeth regression (IA.18), when the interaction term of momentum ranking and u^{IRV}_t is either excluded or included. All t-statistics are reported in the parentheses. The sample period is from January 1985 to January 2019.

Panel A: Currency appreciations and net inflows to the US							
	Portfolio sorting					Fama-MacBeth	
	L	2	3	H	HML	b	b_{rank}
$InFlow^i_t$	0.15	2.07	1.79	1.58	1.44	0.104	0.003
(t)	(0.29)	(4.13)	(3.14)	(4.00)	(2.48)	(1.67)	(1.85)
$InFlow^i_{t+1}$	-0.10	2.02	1.78	1.88	1.98	0.189	0.005
(t)	(-0.21)	(4.42)	(3.87)	(4.46)	(3.41)	(3.30)	(3.87)
$InFlow^i_{t+2}$	-0.23	2.08	2.17	1.52	1.75	0.161	0.004
(t)	(-0.52)	(3.71)	(4.89)	(3.77)	(2.94)	(2.72)	(2.86)
$InFlow^i_{t+3}$	-0.13	1.79	1.87	1.90	2.03	0.185	0.004
(t)	(-0.31)	(4.00)	(3.62)	(5.08)	(4.05)	(3.52)	(3.71)

Panel B: Impact of global IRV					
	γ_1	γ_2	γ_3	β_0	β_1
	0.094	0.098	0.035	0.003	-0.017
(t)	(5.24)	(5.88)	(2.12)	(2.66)	(-2.05)

where I also control for lagged flows. We expect β_0 to be positive but β_1 to be negative so that unexpected increase in the global IRV would impede the inflows to the US. Panel B of Table A1 confirms such prediction and the results are significant. Shocks to the global IRV depreciate high momentum currencies so that the US assets become less attractive for foreign investors, leading to lower inflows to the US.

D. Supplementary results

TABLE A2

Diagnostic for currency SDF

The table replicates Table 1 in Nucera et al. (2023) over the sample period from January 1985 to December 2017. ω is set to 20.

	$\overline{\sigma}^2_\epsilon$	$\overline{RMS}_\alpha$	$R^2(\%)$	MAE		SR	ΔSR	$\hat{b}_{MV,k}$	$\mu_{F,k}$
$\varphi(F_1)$	23.43	1.79	74.64	1.03	F_1	0.47	0.47	0.08	23.80
$\varphi(F_{1-2})$	19.85	1.40	96.02	0.28	F_2	1.28	0.81	1.01	11.62
$\varphi(F_{1-3})$	17.38	0.81	99.30	0.11	F_3	1.60	0.32	0.88	8.65
$\varphi(F_{1-4})$	15.73	0.69	99.56	0.09	F_4	1.66	0.06	0.49	3.29
$\varphi(F_{1-5})$	14.19	0.67	99.59	0.09	F_5	1.67	0.01	0.20	1.25
$\varphi(F_{1-6})$	12.94	0.67	99.59	0.09	F_6	1.67	0.01	0.04	0.18

TABLE A3

Statistics of carry and momentum portfolios; pre- and post-crisis sample

The table reports the statistics for the currency carry and momentum portfolios. Carry portfolios are obtained by sorting on the forward discounts, and momentum portfolios are obtained by sorting on the realized excess returns over the previous three months. All portfolios are rebalanced monthly and the reported average monthly excess returns (in percentage) are net of transaction costs. Exposures to the risk of global IRV are computed from Equation (4). t-statistics are in parentheses and based on Newey and West (1987) with optimal lag selection following Andrews (1991). The excess returns, betas to the dollar factor and the risk of IRV, and monthly Sharpe ratios (SR) of high-minus-low portfolios are also reported. The monotonicity of portfolio excess returns and IRV betas are tested via the monotonic relation (MR) test of Patton and Timmermann (2010), where the p-values are reported in parentheses based on all pair-wise comparisons. The null hypotheses for the tests are the monotonically increasing returns and decreasing betas respectively. The sample period is from January 1985 to January 2019.

	Pre-crisis (1985M1 to 2006M12)		Post-crisis (2007M1 to 2019M1)	
	$r^e_{carry}(\%)$	$r^e_{mom}(\%)$	$r^e_{carry}(\%)$	$r^e_{mom}(\%)$
L	-2.63	-2.05	-2.60	-0.50
	(-1.78)	(-1.08)	(-1.17)	(-0.17)
2	0.89	1.74	-0.93	-2.60
	(0.63)	(1.07)	(-0.41)	(-1.08)
3	5.00	4.62	1.14	0.72
	(2.98)	(2.68)	(0.38)	(0.34)
4	5.14	4.34	-0.24	1.16
	(2.77)	(2.30)	(-0.08)	(0.51)
H	7.44	7.34	3.98	2.37
	(3.16)	(3.59)	(0.99)	(0.98)
HML	10.07	9.39	6.58	2.87
	(4.46)	(4.21)	(2.25)	(1.07)
SR	1.05	0.80	0.68	0.31

TABLE A4

Statistics of alternative momentum portfolios

Panel A reports the statistics for the currency momentum portfolios, which are obtained by sorting on the realized excess returns over the previous 1- and 6-month periods. Alternatively, I form the momentum portfolios by sorting on the changes in log spot rates over the previous 1- and 3-month periods. All portfolios are rebalanced monthly, and the average monthly excess returns (in percentage) are net of transaction costs. The exposures to the risk of global IRV are computed from Equation (4). The t-statistics are in parentheses and based on Newey and West (1987) with optimal lag selection following Andrews (1991). The returns and IRV betas of high-minus-low portfolios are also reported. Panel B reports the results of asset pricing tests by using either momentum portfolios or the joint cross-section of carry and momentum portfolios. The sample period is from January 1985 to January 2019.

	Mom 1-1			Mom 6-1			Mom 1-1 (spot)		
	Panel A: Portfolio statistics								
	r^e	β_{IRV}		r^e	β_{IRV}		r^e	β_{IRV}	
L	-3.24	2.59		-2.28	3.10		-0.26	1.56	
	(-1.80)	(3.50)		(-1.19)	(5.00)		(-0.15)	(2.17)	
2	1.08	2.40		0.84	1.80		-0.12	2.64	
	(0.75)	(3.33)		(0.58)	(3.00)		(-0.08)	(3.67)	
3	0.84	0.84		0.85	0.12		0.72	0.72	
	(0.58)	(1.17)		(0.58)	(0.17)		(0.11)	(1.20)	
4	2.40	-2.76		1.44	-1.56		1.44	-2.04	
	(1.67)	(-4.60)		(1.00)	(-2.17)		(1.00)	(-2.83)	
H	3.84	-3.05		4.44	-3.48		2.82	-3.00	
	(2.46)	(-3.13)		(2.85)	(-3.22)		(1.77)	(-3.13)	
HML	7.08	-5.64		6.72	-6.58		3.08	-4.56	
	(4.21)	(-3.92)		(3.73)	(-5.00)		(1.86)	(-2.71)	
	Panel B: Asset pricing test								
	λ_{DOL}	λ_{IRV}	R^2	λ_{DOL}	λ_{IRV}	R^2	λ_{DOL}	λ_{IRV}	R^2
	0.08	-0.80	0.64	0.08	-0.86	0.86	0.08	-0.49	0.87
(NW)	(0.80)	(-3.81)		(0.80)	(-3.31)		(0.80)	(-1.88)	
(NW-GMM)	(0.72)	(-2.61)		(0.71)	(-2.82)		(0.71)	(-1.46)	
(Sh)	(0.80)	(-2.96)		(0.80)	(-2.53)		(0.80)	(-1.69)	
χ^2_{NW}	[0.01]			[0.11]			[0.69]		
χ^2_{NW-GMM}	[0.11]			[0.25]			[0.71]		
χ^2_{Sh}	[0.07]			[0.33]			[0.76]		
	Joint with carry								
	0.08	-0.99	0.75	0.08	-1.04	0.84	0.08	-0.87	0.74
	0.08	-0.99	0.75	0.08	-1.04	0.84	0.08	-0.87	0.74
(NW)	(0.80)	(-4.50)		(0.80)	(-4.00)		(0.80)	(-4.56)	
(NW-GMM)	(0.77)	(-2.82)		(0.78)	(-2.53)		(0.77)	(-3.16)	
(Sh)	(0.80)	(-3.30)		(0.80)	(-2.74)		(0.80)	(-3.48)	
χ^2_{NW}	[0.00]			[0.00]			[0.06]		
χ^2_{NW-GMM}	[0.11]			[0.18]			[0.32]		
χ^2_{Sh}	[0.14]			[0.20]			[0.39]		

TABLE A5

IRV betas of FX momentum under different limits to arbitrage

The table reports the statistics for the currency momentum portfolios under different limits to arbitrage. I run double sort based on currency's idiosyncratic volatility (or skewness) and realized excess returns over the past 1-, 3- and 6-month horizons to obtain 2×3 portfolios. All portfolios are rebalanced monthly, and the average monthly excess returns (in percentage) are net of transaction costs. The exposures to the risk of global IRV are computed from Equation (4). The t-statistics are in parentheses and based on Newey and West (1987) with optimal lag selection following Andrews (1991). The returns and IRV betas of high-minus-low portfolios are also reported. The sample period is from January 1985 to January 2019.

	Low idvol		High idvol		Low idskew		High idskew	
	r^e	β_{IRV}	r^e	β_{IRV}	r^e	β_{IRV}	r^e	β_{IRV}
				Panel A: Mom 1-1				
L	0.48	2.64	-3.96	2.04	-2.40	2.64	-0.84	3.12
	(0.36)	(2.44)	(-2.20)	(2.13)	(-1.54)	(2.44)	(-0.50)	(2.89)
2	1.08	0.60	1.80	-2.16	1.20	-0.36	1.56	-0.48
	(0.82)	(1.25)	(1.07)	(-2.25)	(0.77)	(-0.33)	(1.18)	(-0.57)
H	2.62	-2.64	3.29	-3.36	1.92	-2.04	3.24	-3.60
	(1.75)	(-3.14)	(2.13)	(-2.15)	(1.14)	(-1.89)	(2.25)	(-3.00)
HML	2.14	-5.28	7.25	-5.40	4.32	-4.68	4.08	-6.72
	(1.14)	(-3.38)	(3.75)	(-2.37)	(2.25)	(-2.60)	(2.13)	(-3.50)
				Panel B: Mom 3-1				
L	-1.92	2.16	-3.00	1.08	-2.40	2.34	-1.62	-1.10
	(-1.23)	(1.80)	(-1.56)	(1.13)	(-1.54)	(2.63)	(-0.86)	(-0.75)
2	1.56	0.24	0.84	-1.32	1.08	0.36	1.44	-0.48
	(1.18)	(0.50)	(0.54)	(-1.38)	(0.82)	(0.38)	(1.09)	(-0.67)
H	3.00	-1.44	4.25	-3.12	2.28	-2.10	5.82	-2.30
	(2.27)	(2.00)	(2.50)	(-3.71)	(1.38)	(-2.13)	(4.00)	(-3.33)
HML	4.92	-3.60	7.25	-4.20	4.68	-4.44	7.44	-1.20
	(3.15)	(-0.25)	(3.81)	(-3.50)	(2.79)	(-4.11)	(4.13)	(0.50)
				Panel C: Mom 6-1				
L	-0.84	2.16	-2.76	0.72	-1.56	2.52	-1.32	-2.40
	(-0.54)	(1.80)	(-1.44)	(0.86)	(-0.93)	(2.63)	(-0.85)	(-1.33)
2	1.56	0.24	2.04	3.01	1.82	1.56	1.32	0.84
	(1.18)	(0.50)	(1.31)	(2.27)	(1.36)	(1.63)	(1.00)	(1.17)
H	2.57	-0.96	2.88	-4.56	1.32	-2.76	4.56	-2.88
	(1.83)	(-1.33)	(1.79)	(-3.80)	(0.85)	(-1.77)	(2.92)	(-1.50)
HML	3.41	-3.12	5.64	-5.28	2.88	-5.28	5.88	-0.48
	(1.67)	(-2.42)	(2.61)	(-4.55)	(1.73)	(-3.82)	(3.31)	(-0.25)

FIGURE A.1

Cumulative returns of FX carry and momentum strategy

The figure plots the cumulative returns of FX carry and momentum strategies. The sample period is from January 1985 to January 2019.

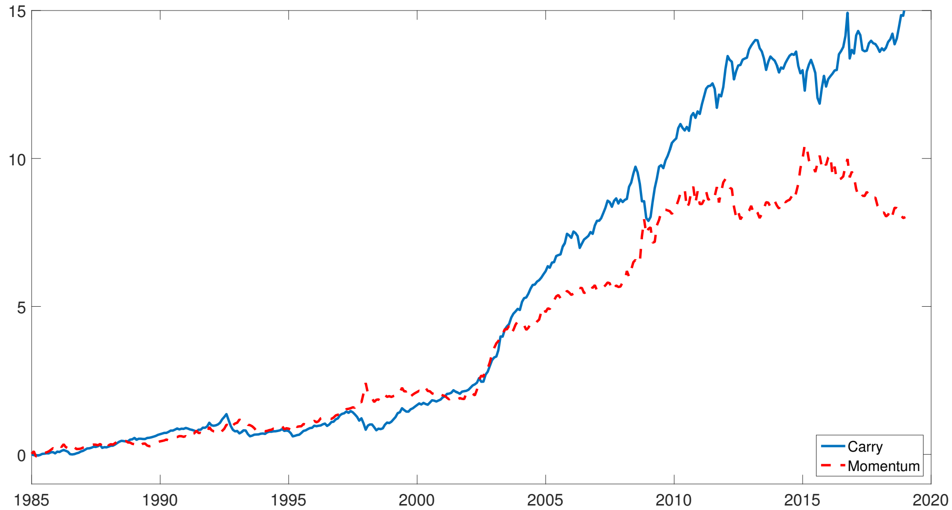
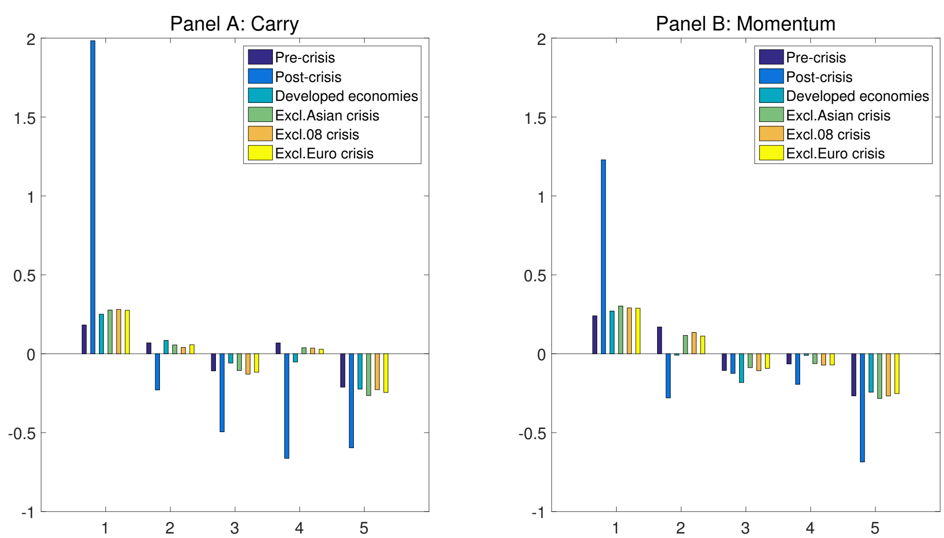


FIGURE A.2

IRV **betas under subsamples**

The figure plots the betas of carry and momentum portfolio returns to the global IRV risk, estimated from Equation (4) by using data from different subsamples. The full sample period is from January 1985 to January 2019.



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