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RMB exchange rate volatility and the cross-section of Chinese A-share returns

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ABSTRACT

This study investigates the role of RMB exchange rate volatility in the cross-sectional pricing of Chinese A-share stocks. We find an inverted U-shaped relation between stock beta-loading on exchange rate volatility (FXV-beta) and future stock returns; that is, both stocks with high FXV-beta and those with low FXV-beta have lower future returns. We show that the underperformance of high-FXV-beta stocks is primarily driven by hedging demand. Specifically, to hedge exchange rate volatility risk, rational investors are willing to pay higher prices for high-FXV-beta stocks and accept lower future returns. We also provide evidence that the underperformance of low-FXV-beta stocks could be due to mispricing dominated by lottery investors.

1. Introduction

The impact of foreign exchange rate risk on stock returns has long been a controversial topic in the field of asset pricing. Solnik (1974), Stulz (1981), and Adler and Dumas (1983) demonstrate theoretically that a stock's covariance with currency returns should affect its expected returns in a world where purchasing power parity is violated. Numerous empirical studies have examined this theoretical prediction, but no consensus has been reached. Some studies provide supporting evidence that exchange rate risk is priced in the stock market (see, e.g., De Santis and Gerard, 1998; Vassalou, 2000; Kolari et al., 2008; Balvers and Klein; 2014), while others argue that the effect remains inconclusive (see, e.g., Jorion, 1991; Griffin, 2002; Carrieri et al., 2006; Francis et al., 2008).

The existing literature primarily focuses on the role of exchange rate changes or returns in stock pricing but pays little attention to the effect of exchange rate volatility, i.e., the second-order moment of the exchange rate. Menkhoff et al. (2012) show that global FX volatility is a powerful risk factor in explaining the cross-sectional variation in currency carry trade returns and it also performs well for pricing several other assets, such as individual currencies, corporate bonds, and equity momentum portfolios. These findings indicate that the pricing power of exchange rate volatility is to some extent pervasive and therefore may apply equally to the cross-sectional returns of individual stocks. Merton (1973) proposes an intertemporal capital asset pricing model (ICAPM) and shows that in a multi-period economy, investors' current demands are influenced by the possibility of uncertain shifts in future investment opportunities. This implies that a state variable that is associated with changes in the investment opportunity set should be priced in the stock market

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and thus stocks' covariances with this state variable should be related to their future returns. Early studies have provided substantial evidence that changes in exchange rate volatility have spillover effects on the stock market, thereby correlating with the risk and value of firms (see, e.g., Hodder, 1982; Hekman, 1985; Roll, 1992; Brown, 2001; Dominguez and Tesar, 2006; Pavlova and Rigobon, 2007). We thus argue that exchange rate volatility should be a state variable as claimed by Merton (1973), which affects future investment opportunities.

Inspired by the aforementioned studies, this paper investigates the role of Renminbi (RMB) exchange rate volatility in the cross-sectional pricing of Chinese A-shares. We study the Chinese market for the following reasons. First, since July 2005, when China reformed its exchange rate regime and de-pegged the RMB from the US dollar, the RMB exchange rate has become increasingly market-oriented and volatile. Prior studies show that after the reform, the spillover effect of RMB exchange rate fluctuations on the stock market has significantly intensified (see, e.g., Chen et al., 2022; Chen et al., 2023). Hence, it is reasonable to further examine whether the volatility of the RMB exchange rate affects stock pricing as predicted by the ICAPM theory.

Second, while the RMB exchange rate remains partially managed rather than fully free-floating, previous literature on exchange rate regimes suggests that even highly managed exchange rates fail to insulate firms from foreign exchange exposure and may even amplify the exposure (see, e.g., Parsley and Popper, 2006; Chue and Cook, 2008; Patnaik and Shah, 2010; Ye et al., 2014).[1] This is because low exchange rate flexibility is often deemed as an implicit government guarantee against short-term exchange rate movements, prompting firms to hold unhedged foreign exchange exposure (Burnside et al., 2001; Patnaik and Shah, 2010; Schneider and Tornell, 2004). Another reason is that under a managed exchange rate regime, firms tend to underestimate currency fluctuations and thus have less incentive to hedge foreign exchange exposure (Ye et al., 2014). Existing studies on the role of exchange rates in stock pricing mostly focus on developed markets with freely floating exchange rates, such as the US (e.g., Du and Hu, 2012; Du and Hu, 2014). However, as mentioned above, exchange rate volatility may have a more pronounced effect on the risk and value of firms in emerging markets, where exchange rates are regulated to varying degrees. Motivated by this point, this paper focuses on China, the largest emerging market, to provide new evidence for the relationship between foreign exchange risk and equity returns.

In this paper, RMB exchange rate volatility is calculated as the mean of the absolute daily log returns on the RMB index of Wu et al. (2019) over the past 20 days.[2] The RMB index is constructed using bilateral exchange rates between the RMB and six representative foreign currencies—i.e., the US dollar, British pound, Euro, Singapore dollar, Japanese yen, and Korean won. We estimate stock exposure to the RMB exchange rate volatility (hereinafter FXV-beta) by regressing excess stock returns on RMB exchange rate volatility innovations over a 60-day rolling window. Our sample contains all A-share stocks traded on China's main board market and growth enterprise market from January 2006 to December 2020, excluding financial firms.

To examine the impact of RMB exchange rate volatility on stock pricing, we perform univariate portfolio-level analyses, in which stocks are sorted into decile portfolios based on their prior-month FXV-beta measures. The results indicate an inverted U-shaped relation between FXV-beta and future stock returns, i.e., stocks with low FXV-beta and high FXV-beta both have lower future returns. The risk-adjusted returns of the FXV-beta-sorted decile portfolios also show a consistent inverted U-shaped pattern, indicating that the nonlinear relation between FXV-beta and future returns cannot be explained by the well-known pricing factors.

We then divide stocks' FXV-beta measures into positive and negative groups to explain the underperformance of stocks with high and low FXV-beta separately. We attribute the underperformance of high-FXV-beta stocks to intertemporal hedging demand. The ICAPM framework of Merton (1973) and Campbell (1993, 1996) suggests that investors have an incentive to hedge against changes in exchange rate volatility, as increasing exchange rate volatility implies a deterioration in future investment opportunities. Driven by such hedging demand, investors prefer to hold stocks whose returns are expected to increase with exchange rate volatility. Hence, they are willing to pay higher prices for stocks with high FXV-beta and accept lower future returns. To support the "hedging demand" explanation, we first perform bivariate portfolio sorts and multivariate Fama and MacBeth (1973) regressions to show that the premium for positive FXV-betas is not explained by other pricing effects, including the market beta, downside beta, market value, book-to-market ratio, momentum, short-term reversal, illiquidity, co-skewness, co-kurtosis, idiosyncratic volatility, idiosyncratic skewness, and value-at-risk. Then, we show that the premium for positive FXV-betas changes over time and becomes higher during periods of high exchange rate volatility, when investors' hedging demand is expected to be stronger. Considering the heterogeneity of investor rationality, we argue that the hedging demand for exchange rate volatility changes primarily comes from rational institutional investors rather than less sophisticated individual investors.

For stocks with low FXV-beta whose returns are negatively related to exchange rate volatility, we can hardly attribute their underperformance to risk-based explanations, as theory predicts that risk-averse investors would pay lower prices for these stocks and demand extra compensation in the form of higher expected returns. We thus provide a behavioral explanation, namely that lottery-demand-based price pressure falls heavily on low-FXV-beta stocks, driving their prices up and thereby reducing future returns. To support this argument, we show that the anomaly for negative FXV-betas becomes insignificant after controlling for the lottery demand effect and that the future returns of low-FXV-beta stocks is significantly negative only if these stocks are sufficiently attractive to lottery investors. We also find that the anomalous premium for negative FXV-betas is much higher for stocks with high levels of individual ownership and high arbitrage costs. These results provide further evidence that the relation between negative FXV-beta and future returns could be an outcome of mispricing dominated by less rational individual investors.

[1] These studies show that the foreign exchange exposure of firms under a managed exchange rate regime is much more prevalent and larger in magnitude than under a freely-floating exchange rate regime.

[2] Fig. A1 of the Appendix presents the daily RMB exchange rate volatility from January 2006 to December 2020. The RMB exchange rate volatility series shows an obvious time-varying feature, varying from 0.05 to 0.71, with a mean value of 0.18.

We also conduct a battery of robustness tests. First, we calculate the FXV-beta measure using an alternative RMB index, an alternative exchange rate volatility measure, two alternative factor models, and two alternative widths of the rolling window. We find that there is still an inverted U-shaped relation between future stock returns and these alternative FXV-beta measures. Second, we test the robustness of the pricing power of the FXV-beta in different periods, and our main findings remain unchanged.

This paper contributes to the literature on the role of exchange rates in asset pricing by revealing the pricing power of exchange rate volatility. Our results suggest that investors care about firms' exposure to the second-order moment of the exchange rate and want to hedge against the deterioration in future investment opportunities due to increased exchange rate volatility. Our study also sheds light on the difference in preferences of investors with different levels of rationality for exchange rate volatility exposure, thus highlighting the impact of investor heterogeneity on asset pricing. Moreover, we show that even under a managed exchange rate regime, exchange rate volatility can still be priced in the cross-section of stock returns.

The rest of the paper is organized as follows. Section 2 details the institutional background, i.e., the changes of China's exchange rate regime since 2005. Section 3 describes the data and variables. Section 4 presents the results of asset pricing tests on FXV-beta. Section 5 provides explanations for the inverted U-shaped relation between FXV-beta and future returns. Section 6 conducts robustness checks. Section 7 concludes.

2. Institutional background

For the past two decades, China has implemented two major reforms on the RMB exchange rate regime: the first one is in July 2005 and the second one is in August 2015. The 2005 reform replaced the previous fixed exchange rate system, in which the RMB was pegged to the US dollar, with a managed floating exchange rate system. It is noteworthy that to deal with the global financial crisis, China reversed this reform in 2008—from July 2008 to October 2010 the RMB exchange rate against the US dollar was essentially fixed. The second reform in 2015 announced a shift in the method used to determine the daily central parity rate of the RMB against the US dollar. Prior to the reform, the central parity rate was largely controlled by the People's Bank of China (PBOC). Under the new regime, the central parity rate was to be determined based on the previous day's closing rate and the market demand and supply conditions. To be more specific, in December 2015, the China Foreign Exchange Trade System (CFETS) started to publish the "CFETS RMB Exchange Rate Index", which displays the value of the RMB against a basket of currencies from 13 countries and regions. Since then, a more market-oriented mechanism for determining the central parity rate, which takes into account both the closing rate and the fluctuations of a basket of currencies, has been gradually established.

The past two RMB regime reforms encompasses two primary goals: 1) strengthening the market-based pricing mechanism for the RMB exchange rate; 2) enhancing the flexibility of exchange rate fluctuations. Through the reforms, the marketization level of the RMB has been significantly improved, and its range of fluctuations has been gradually expanded. In May 2007, the floating range was slightly widened from 0.3 % to 0.5 %. On April 21, 2012, the central bank announced an expansion of the floating range for the interbank foreign exchange market rate to 1 %. In April 2014, the daily fluctuation range of the exchange rate was further expanded to 2 %. Hence, it is becoming increasingly imperative to investigate the influence of the foreign exchange rate volatility on the capital markets in China.

3. Data and variables

Our study begins by measuring the extent to which individual stocks are exposed to the RMB exchange rate volatility. Based on the Chinese four-factor model (CH4) developed by Liu et al. (2019), we estimate the exchange rate volatility exposure for each stock using the following regression specification:

$$R_{i,t} - R_{ft} = \alpha_i + \beta_{1i}MKT_t + \beta_{2i}SMB_t + \beta_{3i}VMG_t + \beta_{4i}PMO_t + \beta_i^{FXV}\Delta Vol_t + \varepsilon_{i,t} \quad (1)$$

where $R_{i,t}$ denotes the return of stock i on day t; R_{ft} denotes the risk-free rate (i.e., the one-year deposit rate); MKT_t, SMB_t, VMG_t and PMO_t are the daily returns on the market, size, earnings-price, and turnover factors, respectively; ΔVol_t is the RMB exchange rate volatility innovations measured by the $AR(1)$ residuals of the exchange rate volatility level; and the coefficient β_i^{FXV} represents the sensitivity of stock i to the RMB exchange rate volatility (hereinafter FXV-beta).

Eq. (1) is estimated monthly for individual stocks using a three-month rolling window. Specifically, at the end of each month, we use daily data for the past three months (a total of 60 trading days) to estimate Eq. (1) and then obtain the stock-level values of β^{FXV} for that month. The three-month estimation period must have at least 50-day valid return observations.

In the empirical analysis, we control for several firm characteristics and risk factors that have been confirmed to be priced in the stock market by the prior literature. Our control variables include the market beta (β^{MKT}), the downside beta (β^{Down}) of Bawa and Lindenberg (1977), the market value (*Size*) and book-to-market ratio (*BM*) of Fama and French (1992, 1993), the medium-term momentum (*Mom*) of Jegadeesh and Titman (1993), the short-term reversal (*Rev*) of Jegadeesh (1990), the illiquidity measure (*Illiq*) of Amihud (2002), the idiosyncratic volatility (*IdioVol*) and idiosyncratic skewness (*IdioSkew*) of Ang et al. (2006), the co-skewness (*CoSkew*) and co-kurtosis (*CoKurt*) of Harvey and Siddique (2000), and the value-at-risk (*VaR*) of Atilgan et al. (2020). All the control variables are calculated at a monthly frequency from December 2005 to November 2020. Table A1 of the Appendix shows the definitions of these control variables.

Our data on stock transactions, financial statements, institutional shareholdings, and analyst report coverage are from Wind Information Inc (WIND). The data on the market, size, value, profitability, and investment factors of Fama and French (1993, 2015) and

Table 1
One-way sorted portfolio analysis. For each month from January 2006 to December 2020, stocks are sorted into decile portfolios based on their FXV-betas (β^{FXV}), where decile 10 (1) includes stocks with the highest (lowest) values of β^{FXV} in the previous month. For each decile, Panel A of Table 1 reports the average value of β^{FXV} (Estimate) and the average percentage of stocks with positive β^{FXV} (Percent Pos.). Panels B and C report the average excess returns and alphas (α_{CH4} and α_{FFC6}) for the equal-weighted and value-weighted portfolios, respectively. The last column of the table shows the return and alpha spreads between decile 10 (High) and decile 1 (Low). Newey-West adjusted *t*-statistics are in parentheses.

Decile	Low	2	3	4	5	6	7	8	9	High	High-Low
Panel A: β^{FXV}											
Estimate	−0.60	−0.34	−0.25	−0.16	−0.09	0.02	0.10	0.18	0.29	0.56	
Percent Pos.	0.00	0.00	0.00	0.00	0.10	0.85	1.00	1.00	1.00	1.00	
Panel B: Equal-weighted portfolios											
Excess Ret.	0.23	0.65	0.79	0.86	0.89	0.84	0.76	0.81	0.66	−0.06	−0.29
	(0.25)	(0.66)	(0.84)	(0.94)	(0.96)	(0.90)	(0.83)	(0.87)	(0.70)	(−0.08)	(−1.12)
α_{CH4}	−0.97	−0.63	−0.43	−0.46	−0.45	−0.58	−0.57	−0.60	−0.52	−1.21	−0.24
	(−3.73)	(−3.79)	(−2.75)	(−2.87)	(−3.31)	(−4.31)	(−3.56)	(−3.60)	(−3.54)	(−4.44)	(−1.29)
α_{FFC6}	−0.32	0.06	0.16	0.19	0.19	0.10	0.09	0.08	−0.11	−0.50	−0.18
	(−2.19)	(0.55)	(1.53)	(1.98)	(2.10)	(0.93)	(0.78)	(0.74)	(−0.83)	(−2.87)	(−1.34)
Panel C: Value-weighted portfolios											
Excess Ret.	0.09	0.57	0.63	0.69	0.80	0.60	0.65	0.68	0.55	−0.34	−0.43
	(0.13)	(0.59)	(0.69)	(0.74)	(0.90)	(0.64)	(0.72)	(0.70)	(0.57)	(−0.37)	(−1.26)
α_{CH4}	−1.22	−0.69	−0.65	−0.78	−0.84	−0.88	−0.55	−0.85	−0.72	−1.54	−0.32
	(−4.06)	(−2.61)	(−3.23)	(−3.04)	(−3.82)	(−3.78)	(−2.56)	(−3.25)	(−2.75)	(−4.78)	(−1.37)
α_{FFC6}	−0.37	0.25	0.13	0.21	0.15	0.02	0.05	0.06	0.14	−0.57	−0.20
	(−2.30)	(1.64)	(0.96)	(1.24)	(1.00)	(0.12)	(0.31)	(0.30)	(0.91)	(−3.32)	(−1.53)

the momentum factor of Carhart (1997) are from the China Stock Market & Accounting Research Database (CSMAR). The one-year deposit rate and the factor return series of Liu et al. (2019) are obtained from the researchers' website.[3] Our sample includes all A-share stocks traded on the main boards of the Shenzhen and Shanghai securities exchanges as well as the board of the Growth Enterprise Market. All financial firms are excluded. The sample period is from January 2006 to December 2020.[4]

Wu et al. (2019) develop a novel RMB index based on both trade and investment weighting and show that it is an effective measure of the comprehensive exchange rate of the RMB. To construct the index, six representative currencies are selected, i.e., the US dollar, British pound, Euro, Singapore dollar, Japanese yen, and Korean won, as these currencies are issued (or used) by countries that account for a large share of bilateral trade with China and have high levels of direct investment in China. We obtain this index from the website of the China Society of Macroeconomics (CSM) and use it to calculate the RMB exchange rate volatility.[5] Specifically, we first calculate the daily log returns on the RMB index (denoted by R^{RMB}). Then, the RMB exchange rate volatility (*Vol*) on day *t* is defined as the mean of the absolute values of R^{RMB} over the past month (a total of 20 trading days). Formulaically,

$$Vol_t = \frac{1}{20}\sum_{i=0}^{19}|R_{t-i}^{RMB}| \quad (2)$$

4. The cross-section of FXV-beta and expected stock returns

The monthly FXV-beta (β^{FXV}) of each stock is estimated from the time-series regressions of daily excess stock returns on daily RMB exchange rate volatility innovations over a three-month rolling window. We obtain the first set of β^{FXV} metrics (for December 2005) using the samples from October to December 2005. Then, these β^{FXV} metrics are used to predict the cross-sectional variation of stock returns for the next month (January 2006). This procedure is repeated month by month until the final sample in December 2020. The results of predictability for cross-sectional returns are reported from January 2006 to December 2020.

We first investigate the relation between FXV-beta and future stock returns through univariate portfolio-level analyses. The results are presented in Table 1. We sort individual stocks into decile portfolios based on their FXV-betas, where decile 10 includes stocks with the highest β^{FXV} over the prior month and decile 1 includes stocks with the lowest β^{FXV} over the prior month. The portfolios are rebalanced every month. For each decile, Panel A of Table 1 reports the average value of β^{FXV} and the average percentage of stocks with positive β^{FXV}. Panels B and C of Table 1 report the time-series averages of excess returns and alphas for the equal-weighted and value-weighted portfolios, respectively.

[3] See https://finance.wharton.upenn.edu/~stambaug/.

[4] Our analysis begins in January 2006 for the following two reasons. First, it was not until July 21, 2005, that the RMB was allowed to float against a basket of currencies in a managed manner. Before that, the RMB was pegged only to the US dollar. Second, to exclude the impact of the change in foreign exchange policy on the stock market, we discard the data with potential noise from July to December 2005.

[5] See https://www.macrochina.com.cn/.

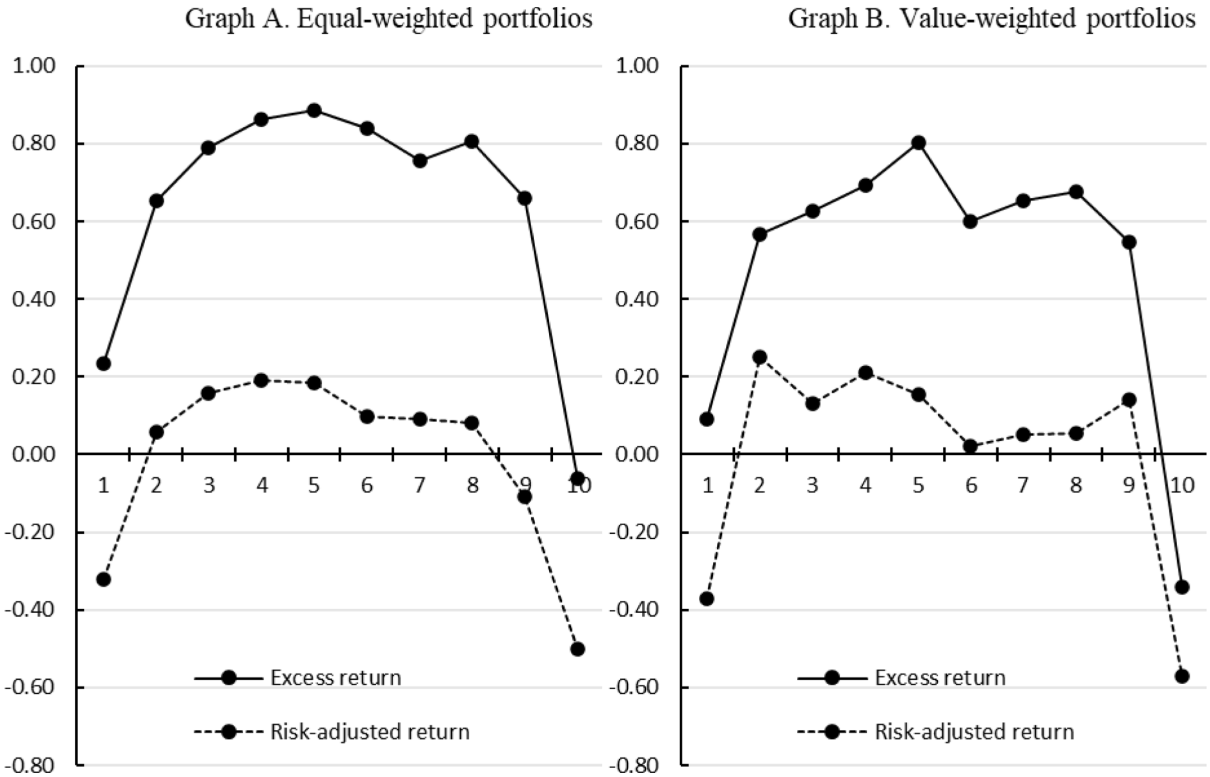

Fig. 1. Average returns on decile portfolios sorted by FXV-beta. Individual stocks are sorted into decile portfolios based on their FXV-betas (β^{FXV}), where decile 10 (1) includes stocks with the highest (lowest) values of β^{FXV} in the previous month. In Fig. 1, the solid line depicts the time-series averages of the monthly excess returns on each of the ten β^{FXV}-sorted portfolios, and the dashed line depicts the risk-adjusted returns on these portfolios, which are calculated based on the 6-factor model (FFC6). Graphs A and B plot returns for the equal-weighted and value-weighted portfolios, respectively.

As shown in Panel A, there exists a large cross-sectional variation in the average FXV-beta from decile 1 to decile 10; the average value of β^{FXV} increases from −0.60 to 0.56. In deciles 1 to 4, all stocks have a negative FXV-beta, while in deciles 7 to 10, all stocks have a positive FXV-beta. Deciles 5 and 6 are transitional groups, with the former consisting mostly of stocks with negative FXV-beta, and the latter consisting overwhelmingly of stocks with positive FXV-beta.

Panel B shows that when moving from the first to the tenth decile of β^{FXV}, the one-month-ahead excess returns for the equal-weighted portfolio initially increase and then decrease. The turning point occurs in the fifth decile, after which the average β^{FXV} value of the portfolio shifts from negative to positive. This result indicates a nonlinear (inverted U-shaped) cross-sectional relation between FXV-beta and expected stock returns; that is, both stocks with high β^{FXV} and those with low β^{FXV} have lower future returns. This inverted U-shaped curve does not appear to be entirely symmetrical. Specifically, the average excess return for decile 1 is 0.23 % per month, whereas that for decile 10 is much lower at −0.06 % per month. The average return spread between deciles 10 and 1 is −0.29 % per month with a Newey and West (1987) *t*-statistic of −1.12.[6]

To investigate whether the inverted U-shaped β^{FXV}-return relation can be explained by specific pricing factors, we also calculate the risk-adjusted returns (alphas) and the corresponding statistical significance for each decile portfolio using two different factor models: (i)α_{CH4} is the alpha of the CH4 model that incorporates the market, size, earnings-price, and turnover factors of Liu et al. (2019); and (ii) α_{FFC6} is the alpha of the 6-factor model (FFC6), consisting of the market, size, and value factors of Fama and French (1993), the momentum factor of Carhart (1997), and the profitability and investment factors of Fama and French (2015). The results show that both of the factor models fail to explain the lower expected returns of high- and low-β^{FXV} stocks. Moving from the lowest to the highest β^{FXV} decile, α_{CH4} and α_{FFC6} for the equal-weighted portfolio also exhibit a trend of first increasing and then decreasing.

Panel C of Table 1 reports the results of value-weighted portfolios and our findings do not change. It is worth noting that the value-weighted 6-factor model alphas for deciles 1 and 10 are −0.37 (*t*-stat. = −2.30) and −0.57 (*t*-stat. = −3.32), respectively, both significantly negative, whereas those for the other deciles are all positive and statistically insignificant. These results suggest that the inverted U-shaped relation between β^{FXV} and expected returns is mainly driven by the underperformance of stocks with the highest and

[6] Taking into account autocorrelation and heteroscedasticity, *t*-statistics are computed using the Newey-West (1987) adjusted standard errors with the optimal number of lags.

Table 2
Two-way sorted portfolio analysis. For each month from January 2006 to December 2020, stocks with positive β^{FXV} are first sorted into three groups (bottom 30%, middle 40%, and top 30%) based on the 30th and 70th percentiles of a given firm-specific attribute. Then, within each firm-specific attribute group, stocks are further sorted into quintile portfolios based on their β^{FXV} measures. We also generate an additional set of quintile portfolios (average group) by averaging β^{FXV} quintile portfolio returns across the three firm-specific attribute groups. Table 2 presents the 6-factor alpha (α_{FFC6}) spreads between the β^{FXV} quintiles 5 and 1 within the bottom, middle, top, and average groups for each firm-specific attribute. Newey-West adjusted *t*-statistics are in parentheses.

	Control variables					
Group	β^{MKT}	*Size*	*BM*	*Mom*	*Rev*	*Illiq*
Bottom	−0.35	−0.52	−0.82	−0.72	−0.33	−0.73
	(−1.06)	(−1.86)	(−2.69)	(−4.08)	(−1.15)	(−2.46)
Middle	−0.71	−0.65	−0.49	−0.44	−0.38	−0.79
	(−3.21)	(−3.14)	(−1.74)	(−2.25)	(−1.97)	(−4.00)
Top	−0.73	−0.54	−0.54	−0.55	−1.00	−0.00
	(−3.25)	(−1.83)	(−2.81)	(−1.93)	(−3.82)	(−0.01)
Avg.	−0.60	−0.57	−0.62	−0.57	−0.58	−0.50
	(−3.50)	(−3.22)	(−3.40)	(−3.41)	(−3.03)	(−2.83)

	Control variables					
Group	*CoSkew*	*CoKurt*	*IdioVol*	*IdioSkew*	*VaR*	β^{Down}
Bottom	−0.36	−0.50	−0.22	−0.58	−0.48	−0.45
	(−1.79)	(−1.63)	(−1.33)	(−2.71)	(−1.87)	(−1.39)
Middle	−0.74	−0.61	−0.31	−0.66	−0.74	−0.91
	(−3.95)	(−3.09)	(−1.52)	(−2.94)	(−3.05)	(−4.91)
Top	−0.74	−0.74	−0.69	−0.65	−0.34	−0.59
	(−2.25)	(−4.33)	(−2.25)	(−2.62)	(−1.05)	(−2.46)
Avg.	−0.61	−0.62	−0.41	−0.63	−0.52	−0.65
	(−3.49)	(−3.76)	(−2.50)	(−3.66)	(−2.86)	(−3.45)

lowest β^{FXV} values. We also plot the excess and risk-adjusted returns of the β^{FXV}-sorted decile portfolios in Fig. 1, from which we can see the inverted U-shaped pattern between β^{FXV} and expected stock returns more clearly.

5. Analysis of the causes of the inverted U-shaped curve

In this section, we investigate the causes of the inverted U-shaped relationship between β^{FXV} and future returns. First, we show the reason why stocks with high β^{FXV} should have lower future returns. Then, we explain why stocks with low β^{FXV} also perform poorly. For subsequent analysis, we generate two additional variables (β^{FXV+} and β^{FXV-}) based on β^{FXV}. β^{FXV+} is equal to β^{FXV} if β^{FXV} is positive and zero otherwise. β^{FXV-} is equal to β^{FXV} if β^{FXV} is negative and zero otherwise.[7]

5.1. Explanation for the right half of the inverted U-shaped curve

Economic theory provides an explanation for the underperformance of stocks with high FXV-beta (decile 10 in Table 1), whose returns are positively correlated with the RMB exchange rate volatility. According to the ICAPM framework of Merton (1973) and Campbell (1993, 1996), investors involved in intertemporal transactions have an incentive to hedge against uncertain shifts in future investment opportunities. Given that early studies have provided substantial evidence of a strong correlation between exchange rate fluctuations and stock market movements (see, e.g., Adler and Dumas, 1983; Ajayi and Mougoué, 1996; Phylaktis and Ravazzolo, 2005; Hau and Rey, 2006; Pavlova and Rigobon, 2007; Fidora et al., 2007), we argue that increased exchange rate volatility would intensify the uncertainty in the stock market and thus lead to adverse changes in the investment opportunity set. To hedge against such adverse changes, investors are more inclined to hold stocks with high positive sensitivities to exchange rate volatility, since these stocks are expected to be safer and even perform better during heightened exchange rate volatility periods. The high demand for stocks with high β^{FXV} raises their current prices and lowers their future returns.

We argue that there is heterogeneity in investors' rationality and that the preference for stocks with high β^{FXV} mainly comes from investors with higher rationality, such as institutional investors. Compared with retail investors who are less rational, institutional investors are better able to capture the elusive information about stock exposure to exchange rate volatility and have greater incentive to hedge against foreign exchange risk.

5.1.1. Two-way sorted portfolio analysis

If the underperformance of high-β^{FXV} stocks is driven by the demand to hedge against changes in future RMB exchange rate

[7] We thank the anonymous referee for this valuable suggestion.

Table 3
Fama-MacBeth regressions. This table presents the time-series averages of the slop coefficients from the following monthly cross-sectional regressions:$\boldsymbol{R}_{i,t+1} = \boldsymbol{\alpha}_t + \boldsymbol{\theta}_t \hat{\text{A}} \cdot \boldsymbol{\beta}^{FXV+}_{i,t} + \boldsymbol{\gamma}_t \hat{\text{A}} \cdot \boldsymbol{X}_{i,t} + \boldsymbol{\varepsilon}_{i,t+1}$, where $\boldsymbol{R}_{i,t+1}$ denotes the excess return of stock $\boldsymbol{i}$ in month $\boldsymbol{t}+1$; $\boldsymbol{\beta}^{FXV+}_{i,t}$ is the one-month lagged $\boldsymbol{\beta}^{FXV+}$ measure of stock $\boldsymbol{i}$; $\boldsymbol{X}_{i,t}$ is a set of control variables observed at the end of month $\boldsymbol{t}$. Regressions in Panel A control for various firm characteristics, including the market beta ($\boldsymbol{\beta}^{MKT}$), log market capitalization (***Size***), book-to-market ratio (***BM***), medium-term momentum (***Mom***), short-term reversal (***Rev***), and illiquidity (***Illiq***). Regressions in Panel B each use all firm characteristics and an additional risk factor, i.e., co-skewness (***CoSkew***), co-kurtosis (***CoKurt***), idiosyncratic volatility (***IdioVol***), idiosyncratic skewness (***IdioSkew***), downside beta ($\boldsymbol{\beta}^{Down}$), or value-at-risk (***VaR***), as controls. The cross-sectional regressions are run for each month from January 2006 to December 2020. $\boldsymbol{R}^2_{adj}$ is the average adjusted R-squared statistic. $\overline{\boldsymbol{n}}$ is the average number of observations available per month. Newey-West adjusted ***t***-statistics are in parentheses.

Panel A: Controlling for firm characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
β^{FXV+}	−1.47	−1.28	−1.27	−1.12	−1.08	−0.94	−0.89
	(−3.71)	(−3.85)	(−4.15)	(−3.98)	(−3.79)	(−3.17)	(−2.91)
β^{MKT}		−0.56	−0.50	−0.67	−0.71	−0.72	−0.23
		(−1.41)	(−1.32)	(−1.85)	(−1.89)	(−1.83)	(−0.63)
Size			−0.46	−0.51	−0.53	−0.43	−0.15
			(−2.68)	(−3.11)	(−3.34)	(−2.52)	(−0.94)
BM				1.74	1.53	1.03	1.09
				(3.31)	(3.30)	(2.19)	(2.32)
Mom					−0.00	−0.01	−0.00
					(−1.22)	(−1.70)	(−1.38)
Rev						−0.07	−0.07
						(−7.34)	(−7.19)
Illiq							0.17
							(3.78)
Intercept	0.77	1.22	11.28	11.95	12.40	10.41	3.24
	(0.83)	(1.35)	(2.82)	(3.08)	(3.33)	(2.56)	(0.84)
R^2_{adj}[%]	0.45	2.28	5.84	7.31	8.26	9.80	10.31
$\overline{n}$	1593	1438	1438	1438	1425	1425	1413

Panel B: Controlling for risk measures

	(1)	(2)	(3)	(4)	(5)	(6)
β^{FXV+}	−0.86	−0.71	−0.88	−0.83	−0.80	−0.64
	(−2.86)	(−2.25)	(−2.83)	(−2.70)	(−2.64)	(−2.17)
β^{Down}	−0.03					
	(−0.09)					
IdioVol		−0.91				
		(−9.52)				
IdioSkew			0.02			
			(0.26)			
				−1.17		
				(−2.41)		
CoKurt					0.50	
					(2.51)	
VaR						0.43
						(5.05)
Intercept	2.83	6.98	3.23	2.71	3.08	4.82
	(0.75)	(1.85)	(0.84)	(0.72)	(0.81)	(1.28)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
R^2_{adj}[%]	10.63	10.85	10.53	10.58	10.83	10.07
$\overline{n}$	1413	1413	1413	1413	1413	1413

volatility, then it should not be explained by other well-known cross-sectional pricing effects, such as β^{MKT}, *Size*, *BM*, *Mom*, *Rev*, *Illiq*, *CoSkew*, *CoKurt*, *IdioVol*, *IdioSkew*, *VaR*, and β^{Down}. To test this conjecture, we perform a series of 3 × 5 bivariate dependent-sort portfolio analyses. Specifically, for each month, we first sort stocks with positive β^{FXV} into three groups—bottom 30 %, middle 40 %, and top 30 %—based on the 30th and 70th percentiles of a given firm-specific attribute (i.e., control variable).[8] Then, within each firm-specific attribute group, stocks are further sorted into quintile portfolios based on their β^{FXV} measures so that quintile 5 includes stocks with the highest values of β^{FXV} and quintile 1 includes stocks with almost zero β^{FXV} (similar to deciles 6 and 7 in Table 1). We also generate an additional set of quintile portfolios (called average group) by averaging β^{FXV} quintile portfolio returns across the three firm-specific attribute groups. Portfolios in the average group are dispersed in β^{FXV}, but all have very similar levels of control variables. Thus, this set of portfolios reflects the relation between β^{FXV} and expected returns after excluding the effect of control variables.

[8] We exclude stocks with negative β^{FXV} in bivariate portfolio sorts to obtain a monotonic cross-sectional relationship between β^{FXV} and futures returns.

Table 2 presents the 6-factor alpha (α_{FFC6}) spreads between the highest and lowest β^{FXV} quintiles within the bottom, middle, top, and average groups of each control variable. The results show that the FXV-beta premium is negative and statistically significant at most levels of the twelve firm-specific attributes.[9] The α_{FFC6} spread between the extreme β^{FXV} quintiles lose significance only in the bottom groups of β^{MKT}, *Rev*, *CoKurt*, and β^{Down}; the top groups of *Illiq* and *VaR*; and the bottom and middle groups of *IdioVol*, but it remains negative. Nevertheless, in the average group of each control variable, the α_{FFC6} spread is consistently significantly negative, with a value ranging from −0.41 % per month to −0.65 % per month and *t*-statistics between −2.50 and −3.76. These results indicate that none of the firm characteristics and risk factors can fully explain the underperformance of stocks with high β^{FXV}.

Table 2 also provides a glimpse into how the relation between β^{FXV} and expected stock returns changes across different levels of control variables. For example, it can be seen that the negative FXV-beta premium is stronger for stocks with high liquidity and high reversal than for stocks with low liquidity and low reversal.

5.1.2. Firm-level cross-sectional regression analysis

So far, we have shown at the portfolio level that the lower future returns of high-β^{FXV} stocks are not the result of other well-known pricing effects. Portfolio-level analysis is a nonparametric technique that imposes no rigid constraints on the nature of the relationship between the variables under study. However, it also has a significant disadvantage, which is the difficulty of accommodating multiple control variables simultaneously. To address this issue, we further utilize multivariate Fama and MacBeth (1973) regressions to test the significance of the FXV-beta premium. For this purpose, we run monthly firm-level cross-sectional regressions with the following specification:

$$R_{i,t+1} = \alpha_t + \theta_t \hat{A} \cdot \beta_{i,t}^{FXV+} + \boldsymbol{\gamma}_t \hat{A} \cdot \boldsymbol{X}_{i,t} + \varepsilon_{i,t+1} \tag{3}$$

where $R_{i,t+1}$ denotes the excess return of stock *i* in month $t+1$; $\beta_{i,t}^{FXV+}$ is the one-month lagged β^{FXV+} measure of stock *i*, which is defined at the beginning of Section 5; and $\boldsymbol{X}_{i,t}$ is a set of firm-specific control variables observed at the end of month *t*.

We estimate Eq. (3) using the ordinary least squares (OLS) method for each month from January 2006 to December 2020 and calculate the time-series averages of the estimated slope coefficients.[10] The results are provided in Table 3. The first column of Table 3, Panel A, shows that when regressing excess stock returns on β^{FXV+} alone, the average slope coefficient on β^{FXV+} is −1.47 with a Newey-West *t*-statistic of −3.71, which is significantly negative. This result is in line with those from portfolio-level analyses in Table 2. To measure the economic magnitude of the slope estimate, we utilize the average FXV-beta values of the univariate decile portfolios. Recall that, in Table 1, the difference in average FXV-betas between decile 10 and decile 6 is 0.54 (= 0.56 −0.02). This indicates that if stocks were to move from the lowest-β^{FXV+} portfolio (decile 6) to the highest-β^{FXV+} portfolio (decile 10), their average expected return would decrease by 0.79 % per month (−1.47 × 0.54 = −0.79), which is quite economically significant. Columns 2 to 7 of Panel A present the results estimated from the multivariate regression specifications, in which various firm characteristics (i.e., the market beta, log market capitalization, book-to-marker ratio, momentum, short-term reversal, and illiquidity) are controlled for stepwise. In these specifications, the slope coefficients on β^{FXV+} remain negative and statistically significant: their values are estimated between −0.89 and −1.28 with *t*-statistics in the range of −2.91 and −4.15. Multiplying these slope coefficients by the FXV-beta difference between deciles 10 and 6 yields estimated annualized premiums between −5.77 % and −8.29 %. These results suggest that the effect of β^{FXV+} on future stock returns remain economically significant after controlling for other firm characteristics.

In panel B, each specification uses a control variable set consisting of all firm characteristics and a risk factor (i.e., downside beta, idiosyncratic volatility, idiosyncratic skewness, co-skewness, co-kurtosis, and value-at-risk). In these specifications, the slope co-efficients on β^{FXV+} are still estimated to be significantly negative, with values ranging from −0.64 to −0.88 and *t*-statistics between −2.17 and −2.86. Collectively, these results indicate that the β^{FXV+} measure provides important, distinct information that is not captured by other firm-specific attributes and it has strong and robust predictive power for future stock returns.

5.1.3. Time-varying feature of FXV-beta premium

We have thus far examined the average effect of positive β^{FXV} on future stock returns over the period of 2006 to 2020 and shown that the negative returns of high-β^{FXV} stocks cannot be explained by other pricing effects. This finding indirectly supports our "intertemporal hedging demand" explanation for the cause of the right half of the inverted U-shaped curve. In this section, we test whether the FXV-beta premium is state-dependent and varies over time. The results of this test will provide more direct evidence for our "intertemporal hedging demand" explanation.

According to the ICAPM theory, if the underperformance of high-β^{FXV} stocks is due to hedging demand, the negative relation between positive β^{FXV} and future stock returns should be time-varying and stronger during periods of high exchange rate volatility (Bekaert et al., 2013; Bali et al., 2017a; Huynh, and Xia, 2021). This is because during such periods, investors would be more concerned about the deterioration in investment opportunities and show stronger hedging demand; thus, they are willing to pay even higher

9 The FXV-beta premium here refers to the premium for the positive loadings on the RMB exchange rate volatility. Unless otherwise specified, the meaning of FXV-beta premium in the rest of the paper is the same.

10 Following Asparouhova et al. (2013) and Atilgan et al. (2020), we also estimate Eq. (3) using the weighted least squares (WLS) method, where the weighting factor equals one plus the one-month lagged return. The results are similar to those estimated using the OLS method. The WLS results are not reported to save space, but are available on request.

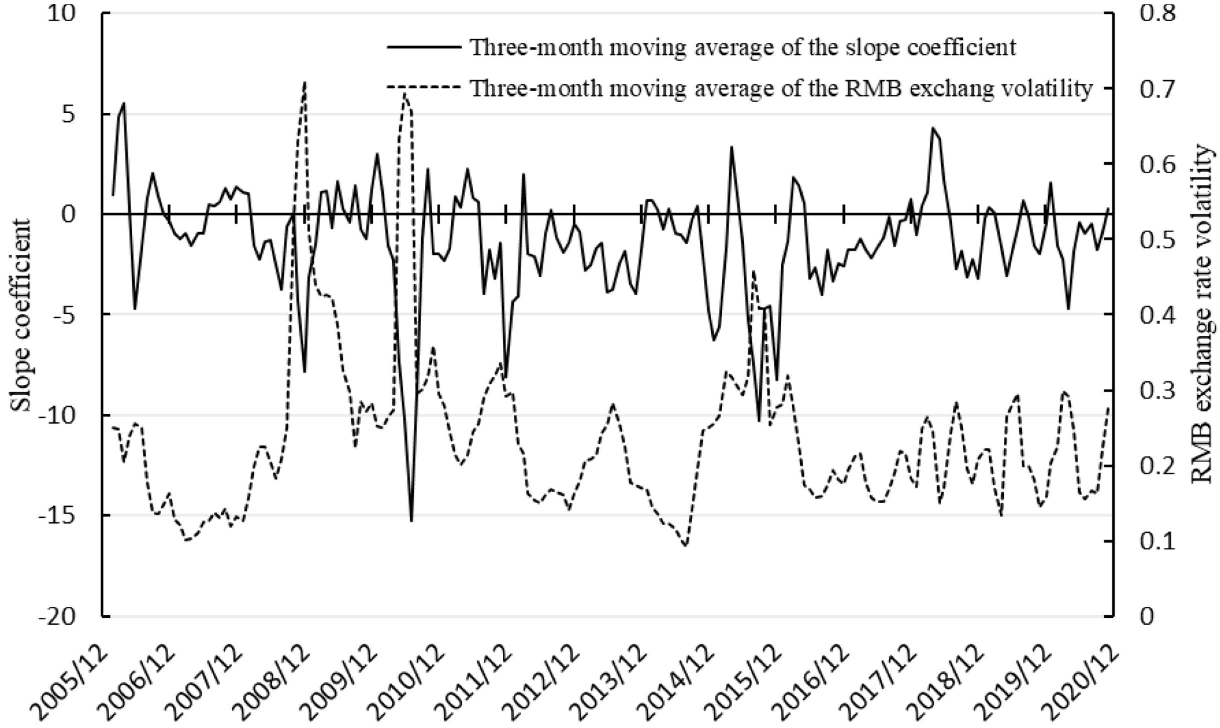

Fig. 2. Slope coefficient on β^{FXV+} and RMB exchange rate volatility. The solid line depicts the three-month moving average of the monthly slope coefficient on β^{FXV+}, which is estimated from the monthly cross-sectional regression of excess stock returns on one-month lagged β^{FXV+} measures. The dashed line depicts the three-month moving average of the monthly RMB exchange rate volatility.

prices and accept even lower returns for stocks with high β^{FXV} for hedging purposes.

To test our conjecture, we run time-series regressions with the following specification:

$$\theta_t = \beta_0 + \beta_1 \hat{A} \cdot vol_t + \epsilon_t \tag{4}$$

where θ_t is the slope coefficient on β^{FXV+} in month t, estimated from Eq. (3); and vol_t is the RMB exchange rate volatility in month t, calculated as the mean of the absolute values of the daily log returns on the RMB index for that month.[11]

We first use θ_t estimated from the univariate regression specification in the first column of Table 3, Panel A, as the dependent variable of Eq. (4). In this case, the slope coefficient on vol_t is estimated to be −3.02 with a t-statistic of −2.21, which is significantly negative. This result suggests that the FXV-beta premium is closely related to the RMB exchange rate volatility. Specifically, an increase of two standard deviations in the RMB exchange rate volatility would result in an average increase of 0.85 % per month in the magnitude of the FXV-beta premium, given that the standard deviation of vol_t is about 0.14. For robustness, we also use θ_t estimated from specification (7) in Table 3, Panel A, as the dependent variable in the regression. Under this change, the slope coefficient on vol_t remains negative and statistically significant, with a value of −2.56 and t-statistic of −1.83.

Fig. 2 plots the three-month moving average of the monthly RMB exchange rate volatility as well as the three-month moving average of the monthly slope coefficient on β^{FXV+}. From this figure, we can observe the time-varying behavior of the FXV-beta premium more clearly. The monthly premium generally moves in the opposite direction of the exchange rate volatility and becomes more negative and larger in magnitude as the exchange rate volatility increases sharply.

Next, we investigate whether the return and alpha differences between the highest and lowest positive-β^{FXV} quintiles become larger when the RMB exchange rate volatility is higher. We sort stocks with positive β^{FXV} into quintile portfolios based on their β^{FXV} measures for each month and then calculate the average return and alpha differences between quintiles 5 and 1 over high and low exchange rate volatility periods separately.[12] High vs. low exchange rate volatility periods are determined based on the median of the monthly RMB exchange rate volatility series. We find that during periods of low exchange rate volatility ($vol_t \leq Median$), the average return difference between quintiles 5 and 1 is −0.53 % per month (t-stat. = −2.28), whereas during periods of high exchange rate volatility ($vol_t > Median$), this difference increases further to −0.97 % per month (t-stat. = −3.66). From the risk-adjusted returns (α_{FFC6}), we

[11] We also calculate the monthly RMB exchange rate volatility as the standard deviation of the daily log returns on the RMB index in each month, and our results do not change.

[12] As with the bivariate portfolio sorts in Section 5.1.1, we do not include negative-β^{FXV} stocks in the current portfolio analysis.

Table 4

Lottery demand. This table examines the "lottery demand" explanation for the underperformance of low-β^{FXV} stocks. Panel A reports the results from Fama-MacBeth regressions of one-month-ahead excess returns on β^{FXV-} and one of the firm characteristics: MAX, β^{MKT}, $Size$, BM, Mom, Rev, and $Illiq$. R^2_{adj} is the average adjusted R-squared statistic. $\overline{n}$ is the average number of observations available per month. Panel B reports the results from univariate portfolio sorts. Each month, stocks are sorted into decile portfolios based on their β^{FXV} measures. We report the 6-factor alpha (α_{FFC6}) of each decile portfolio and the alpha spread between the extreme β^{FXV} deciles for low- and high-$\rho_{MAX,\beta^{FXV-}}$ periods separately. $\rho_{MAX,\beta^{FXV-}}$ is the cross-sectional Pearson correlation coefficient between MAX and β^{FXV-}. The lower the value of $\rho_{MAX,\beta^{FXV-}}$, the stronger the cross-sectional negative correlation between MAX and β^{FXV-}. A month is classified as a low-$\rho_{MAX,\beta^{FXV-}}$ (high-$\rho_{MAX,\beta^{FXV-}}$) period if the value of $\rho_{MAX,\beta^{FXV-}}$ for that month is less than or equal to (greater than) the median $\rho_{MAX,\beta^{FXV-}}$. The sample period spans from January 2006 to December 2020. Newey-West adjusted t-statistics are in parentheses.

Panel A: Fama-MacBeth regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β^{FXV-}	1.19	0.51	1.25	1.34	0.95	1.12	0.83	1.10
	(2.30)	(1.04)	(2.45)	(2.62)	(1.96)	(2.23)	(1.76)	(2.11)
MAX		−0.28						
		(−9.24)						
β^{MKT}			−0.59					
			(−1.50)					
Size				−0.41				
				(−2.45)				
BM					1.54			
					(2.67)			
Mom						−0.00		
						(−1.21)		
Rev							−0.06	
							(−6.19)	
Illiq								0.17
								(3.15)
Intercept	0.68	2.25	1.23	9.63	0.24	0.79	0.62	0.09
	(0.71)	(2.35)	(1.38)	(2.31)	(0.24)	(0.84)	(0.61)	(0.10)
R^2_{adj}[%]	0.49	1.72	2.23	4.40	2.49	2.48	2.90	2.21
$\overline{n}$	1593	1593	1438	1593	1593	1515	1593	1581

Panel B: Univariate portfolios for months with low and high ρ_{MAX,β^-}

	Low	2	3	4	5	6	7	8	9	High	High-Low
Low ρ_{MAX,β^-}	−0.63	0.36	0.21	0.29	0.16	0.08	0.19	−0.05	0.20	−0.49	0.14
	(−2.59)	(1.55)	(0.97)	(1.14)	(0.71)	(0.37)	(0.75)	(−0.17)	(0.81)	(−2.10)	(0.88)
High ρ_{MAX,β^-}	−0.11	0.15	0.04	0.12	0.13	−0.04	−0.09	0.18	0.06	−0.68	−0.56
	(−0.52)	(0.74)	(0.26)	(0.55)	(0.68)	(−0.14)	(−0.45)	(0.67)	(0.36)	(−2.64)	(−2.81)

obtain similar results: the α_{FFC6} difference during low exchange rate volatility periods is −0.45 % per month (t-stat. = −2.52), whereas that during high exchange rate volatility periods is much higher at −0.68 % per month (t-stat. = −4.18).

In summary, our findings suggest that the FXV-beta premium is state-dependent and expands as the RMB exchange rate volatility increases. This further confirms that the underperformance of high-β^{FXV} stocks is driven by hedging demand.

5.2. *Explanation for the left half of the inverted U-shaped curve*

In this section, we discuss the reason for the underperformance of stocks with low FXV-beta (decile 1 in Table 1), whose returns are negatively correlated with the RMB exchange rate volatility. In theory, risk-averse and/or uncertainty-averse investors would pay lower prices for stocks suffering losses as exchange rate volatility increases and require higher expected returns as extra compensation for holding such stocks. However, our previous analyses reveal the opposite of this prediction and show that investors overprice stocks that are highly negatively sensitive to the RMB exchange rate volatility. This result does not fit with risk-based explanations and is more likely to stem from irrational mispricing.

The majority of investors in the Chinese stock market are unsophisticated individual investors who exhibit stronger behavioral tendencies. According to the Shanghai Stock Exchange Statistics Annual 2021, as of the end of 2020, individual investors in China held 22.93 % of the market value of all outstanding A-shares and opened 99.74 % of all trading accounts.[13] As a result, the phenomena of irrationality and mispricing are more pronounced in the Chinese stock market than in developed markets (see, e.g., Chang et al., 2014; Han and Li, 2017). Moreover, due to strict short-sale constraints and capital controls, the overpricing of Chinese A-shares is generally more severe and harder to correct. Given these salient features of the Chinese stock market, we argue that the underperformance of low-β^{FXV} stocks is an outcome of mispricing, which is mainly caused by irrational individual investors. We provide evidence for this

[13] See the Shanghai Stock Exchange website: https://www.sse.com.cn/aboutus/publication/yearly/documents/c/5641852.pdf.

argument from different angles in the following subsections.

5.2.1. Lottery demand

We first examine whether the underperformance of low-β^{FXV} stocks can be attributed to lottery demand. There is evidence that investors have a preference for lottery-type stocks, i.e., stocks with the potential for significant short-term increases in price (Kumar, 2009; Bali et al., 2011; Han and Kumar, 2013). Bali et al. (2017b) suggest that such price increases are partially generated by the sensitivity of a stock to the market factor (i.e., market beta) and show that investors' demand for lottery-type stocks is an important driver of lower future returns for high market beta stocks. Motivated by these studies, we argue that stocks with extremely negative β^{FXV} will also appeal to lottery investors because, with changes in exchange rate volatility, these stocks have a probability of realizing extremely positive daily returns, thus exhibiting lottery characteristics. More specifically, we posit that price pressure exerted by lottery demand falls heavily on low-β^{FXV} stocks, causing these stocks to be overpriced and thus have lower future returns.

To test whether lottery demand has an impact on the anomaly for negative β^{FXV}, we run Fama-MacBeth regressions of future excess returns on the β^{FXV-} measure with and without controlling for the lottery demand effect (*MAX*). The full regression specification is as follows:

$$R_{i,t+1} = \alpha_t + \theta_t \hat{\text{A}} \cdot \beta_{i,t}^{FXV-} + \lambda_t \hat{\text{A}} \cdot MAX_{i,t} + \varepsilon_{i,t+1} \quad (5)$$

where $R_{i,t+1}$ is the excess return of stock *i* in month $t+1$; $\beta_{i,t}^{FXV-}$ is the one-month lagged β^{FXV-} measure of stock *i*, which is defined at the beginning of Section 5; and $MAX_{i,t}$ is calculated as the maximum daily return of stock *i* in month *t*, following Bali et al. (2011).

We run the cross-sectional regressions for each month in our sample period and report the time-series averages of the slope estimates in Panel A of Table 4. As shown in specification (1), the average slope from the monthly regressions of excess returns on β^{FXV-} alone is 1.19 with a *t*-statistic of 2.30, indicating a significantly positive premium for negative FXV-betas. Specification (2) includes *MAX* as a control variable. We find that the slope coefficient on *MAX* is negative, −0.28, and extremely significant with a *t*-statistic of −9.24. This result is consistent with prior studies (e.g., Liu et al., 2023; Zhang et al., 2023), showing that the lottery demand effect is very prominent in the Chinese stock market. However, after controlling for *MAX*, the slope coefficient on β^{FXV-} decreases to 0.51 (*t*-stat. = 1.04), less than half of the value in specification (1), and is no longer statistically significant. This indicates that the underperformance of low-β^{FXV} stocks is in large part driven by lottery demand. In specifications (3) to (8), we also replace *MAX* with β^{MKT}, *Size*, *BM*, *Mom*, *Rev*, and *Illiq*, respectively, as the control variable. In these specifications, the slope coefficients on β^{FXV-} remain significantly positive at least at the 10 % level, with values ranging from 0.83 to 1.34 and *t*-statistics between 1.76 and 2.62; that is, other well-known firm characteristics do not explain the premium for negative FXV-betas as effectively as *MAX*.

We next test our hypothesis by investigating the cross-sectional relation between *MAX* and β^{FXV-}. If low-FXV-beta stocks are also predominantly high-lottery-demand stocks, there should be a strong negative cross-sectional relation between *MAX* and β^{FXV-}. Thus, we calculate the cross-sectional Pearson correlation coefficient between these two variables (denoted by $\rho_{MAX,\beta^{FXV-}}$) each month.[14] We find that out of the 180 months in the sample period, $\rho_{MAX,\beta^{FXV-}}$ is negative for 178 months: values of $\rho_{MAX,\beta^{FXV-}}$ range from −0.45 to 0.04, with a mean of −0.19 and a median of −0.20. These results align with our conjecture, showing that in most months *MAX* and β^{FXV-} are highly negatively correlated.

If lottery demand plays an important role in driving the anomaly for negative FXV-betas, we also expect this anomaly to be more pronounced during low-$\rho_{MAX,\beta^{FXV-}}$ periods and weaker during high-$\rho_{MAX,\beta^{FXV-}}$ periods.[15] This is because during low-$\rho_{MAX,\beta^{FXV-}}$ periods, price pressure from lottery demand should be mostly exerted on stocks with extremely negative β^{FXV}, resulting in significantly lower future returns for these stocks. In contrast, during high-$\rho_{MAX,\beta^{FXV-}}$ periods when *MAX* is not strongly negatively correlated with β^{FXV-}, lottery-demand-based price pressure should be distributed more equally between stocks with extremely negative β^{FXV} and stocks with almost zero β^{FXV}, making the underperformance of the former less pronounced. To test this conjecture, we sort stocks into decile portfolios by their β^{FXV} measures each month and then calculate the average risk-adjusted return (α_{FFC6}) of each portfolio for low- and high-$\rho_{MAX,\beta^{FXV-}}$ periods separately. As shown in Panel B of Table 4, during low-$\rho_{MAX,\beta^{FXV-}}$ periods, the α_{FFC6} on the low-β^{FXV} portfolio is significantly negative with a value of −0.63 % per month and *t*-statistic of −2.59 and the α_{FFC6} difference between the high- and low-β^{FXV} portfolios is statistically insignificant. However, during high-$\rho_{MAX,\beta^{FXV-}}$ periods, the α_{FFC6} on the low-β^{FXV} portfolio shrinks to −0.11 % per month (*t*-stat. = −0.52), which, while still negative, is no longer significant. Moreover, at this time, the α_{FFC6} difference

[14] Stocks with positive β^{FXV} are excluded in the calculation of $\rho_{MAX,\beta^{FXV-}}$.

[15] A month is classified as a low-$\rho_{MAX,\beta^{FXV-}}$ (high-$\rho_{MAX,\beta^{FXV-}}$) period if the value of $\rho_{MAX,\beta^{FXV-}}$ for that month is less than or equal to (greater than) the median $\rho_{MAX,\beta^{FXV-}}$ of −0.20. Note that $\rho_{MAX,\beta^{FXV-}}$ is negative in most months and a lower value of $\rho_{MAX,\beta^{FXV-}}$ indicates a stronger negative correlation between *MAX* and β^{FXV-}.

Table 5
Institutional ownership. First, stocks with negative β^{FXV} are sorted into decile portfolios based on their β^{FXV} measures each month, so that decile 1 includes stocks with the lowest values of β^{FXV} and decile 10 includes stocks with almost zero β^{FXV} in the previous month. Panel A of Table 5 reports the time-series average of the cross-sectional means of the percentage institutional ownership for each of the decile portfolios. The last column of Panel A shows the difference in percentage institutional ownership between deciles 1 and 10. Then, for each month, stocks with negative β^{FXV} are independently sorted into quintiles based on their percentage institutional ownership, and quintiles based on their β^{FXV} measures. Panel B of Table 5 reports the 6-factor alpha (α_{FFC6}) for each of the 25 resulting intersection value-weighted portfolios, as well as the 6-factor alpha on the long-short portfolio that goes long on stocks with almost zero β^{FXV} (quintile 5) and short on stocks with the lowest β^{FXV} (quintile 1) within each institutional ownership (INST) group. The last column of Panel B shows the alpha difference between the long-short portfolios within the extreme INST quintiles (**INST5** −**INST1**). The sample period spans from January 2006 to December 2020. Newey-West adjusted *t*-statistics are in parentheses.

Panel A: Level of institutional ownership

Decile	1	2	3	4	5	6	7	8	9	10	1–10
INST (%)	29.94	32.04	32.50	32.59	33.50	33.65	33.79	33.78	33.79	34.33	−4.39
											(−5.51)

Panel B: Returns of two-way sorted portfolios

	INST1	INST2	INST3	INST4	INST5	INST5-INST1
1	−0.54	−0.20	−0.23	−0.07	0.35	
2	−0.41	0.07	0.11	0.26	0.52	
3	−0.58	0.20	0.02	0.23	0.16	
4	−0.36	0.48	0.36	−0.19	0.40	
5	0.08	0.17	0.17	0.26	0.05	
5–1	0.61	0.37	0.40	0.33	−0.30	−0.91
	(2.22)	(1.55)	(1.70)	(1.28)	(−1.06)	(−2.00)

between the high- and low-β^{FXV} portfolios becomes statistically significant; −0.56 % per month (*t*-stat. = −2.81). These results support our conjecture, indicating that low-β^{FXV} stocks produce significantly lower future returns only when *MAX* and β^{FXV-} are strongly negatively related.

Altogether, our findings suggest that the underperformance of low-β^{FXV} stocks is a manifestation of the effect of lottery demand on stock returns.[16]

5.2.2. Institutional ownership

We next provide evidence for the "lottery demand" explanation from the perspective of institutional ownership levels. Prior studies (Kumar, 2009; Han and Kumar, 2013; Bali et al., 2017b) show that the lottery demand phenomenon is dominated by individual, not institutional, investors. Hence, if the relation between negative β^{FXV} and future stock returns is attributable to lottery demand, this relation should be stronger in stocks that are more actively traded by individual investors compared to those that are more actively traded by institutional investors. Institutional investors are generally more rational than individual investors. They prefer to hold stocks with positive β^{FXV} for hedging purposes and steer clear of stocks with negative β^{FXV}.

With these thoughts in mind, we first examine whether stocks with extremely negative β^{FXV} have lower levels of institutional ownership and thus higher levels of individual ownership. To this end, we sort stocks with negative β^{FXV} into decile portfolios based on their β^{FXV} measures each month and then calculate the time-series average of the cross-sectional means of the percentage institutional ownership for each decile.[17] The results reported in Panel A of Table 5 shows that moving from the tenth to the first decile, the percentage institutional ownership decreases almost monotonically from 34.33 % to 29.94 %. The steepest decline occurs in decile 1, which includes stocks with the strongest negative sensitivity to the RMB exchange rate volatility. The difference in percentage institutional ownership between decile 1 and decile 10 is significantly negative, with a value of −4.39 % and *t*-statistic of −5.51. These results suggest that stocks with extremely negative β^{FXV} are more (less) likely to be held by individual (institutional) investors.

Second, we investigate how the magnitude of the relation between negative β^{FXV} and future returns changes across stocks with different levels of institutional holdings. For this purpose, we sort negative-β^{FXV} stocks in the sample into quintiles based on their percentage institutional ownership at the end of each month. We also independently sort these negative-β^{FXV} stocks into additional quintiles based on their β^{FXV} measures. The two-way sort forms 25 value-weighted portfolios. Panel B of Table 5 presents the 6-factor alpha (α_{FFC6}) for each of the 25 portfolios as well as the 6-factor alpha on the long-short portfolio that goes long on stocks with almost zero β^{FXV} (quintile 5) and short on stocks with the lowest β^{FXV} (quintile 1) within each institutional ownership (INST) group. We find

[16] Considering that high-β^{FXV} stocks may also attract lottery investors, we also examine the impact of lottery demand on the premium for positive FXV-betas by running Fama-MacBeth regressions of future excess returns on the β^{FXV+} measure while controlling for *MAX*. The results show that after controlling for *MAX*, the slope coefficient on β^{FXV+} decreases to some extent in magnitude but remains economically large and statistically significant, with a value of −1.01 and *t*-statistic of −2.55. Thus, lottery demand is not the primary reason for the underperformance of high-β^{FXV} stocks.

[17] Percentage institutional ownership is defined as the fraction of total outstanding shares that are held by institutional investors as of the end of the last fiscal quarter (see Atilgan et al., 2020).

Table 6
Costly arbitrage. Stocks with negative $\boldsymbol{\beta}^{FXV}$ are independently sorted into quintiles based on their arbitrage index (AI) and quintiles based on their $\boldsymbol{\beta}^{FXV}$ measures. The intersections of the five AI and five $\boldsymbol{\beta}^{FXV}$ quintiles generate 25 value-weighted portfolios. Table 6 reports the 6-factor alpha ($\boldsymbol{\alpha}_{FFC6}$) for each of the 25 portfolios, as well as the 6-factor alpha on the long-short portfolio in each AI group that goes long on stocks with almost zero $\boldsymbol{\beta}^{FXV}$ (quintile 5) and short on stocks with the lowest values of $\boldsymbol{\beta}^{FXV}$ (quintile 1). The bottom right corner of the table presents the alpha difference between the long-short portfolios within the extreme AI quintiles (**AI5** −**AI1**). The last column of the table also reports the alpha difference between the AI5 and AI1 quintiles within each $\boldsymbol{\beta}^{FXV}$ group. The sample period spans from January 2006 to December 2020. Newey-West adjusted ***t***-statistics are in parentheses.

	AI1	AI2	AI3	AI4	AI5	AI5-AI1
1	0.17	−0.13	−0.26	−0.29	−0.66	−0.83
						(−2.26)
2	0.22	0.17	−0.11	0.19	−0.30	−0.52
						(−1.67)
3	−0.06	0.52	0.35	0.15	−0.12	−0.06
						(−0.13)
4	−0.13	0.33	0.28	0.27	−0.05	0.08
						(0.29)
5	0.04	0.14	0.23	0.12	0.18	0.14
						(0.24)
5–1	−0.13	0.27	0.49	0.41	0.84	0.97
	(−0.38)	(1.07)	(1.73)	(1.61)	(2.35)	(2.16)

that the α_{FFC6} of the long-short portfolio in the first INST quintile (which contains stocks with the lowest level of institutional ownership) is significantly positive with a value of 0.61 % per month and *t*-statistic of 2.22, whereas the α_{FFC6} of the long-short portfolio in the fifth INST quintile (which contains stocks with the highest level of institutional ownership) turns out to be negative, −0.30 % per month (*t*-stat. = −1.06), and statistically insignificant. The α_{FFC6} spread between the two long-short portfolios (INST5 −INST1) is significantly negative; −0.91 % per month with a *t*-statistic of −2.00. Collectively, these results validate our conjecture, showing that the anomaly for negative β^{FXV} is more pronounced for stocks with lower (higher) levels of institutional (individual) holdings.

5.2.3. Costly arbitrage

The mispricing hypothesis also predicts that the anomalous positive relation between negative β^{FXV} and future returns should be more pronounced for stocks with higher arbitrage costs as investors are less willing (or able) to fully update these stocks' prices (Cao and Han, 2016; Beneish et al., 2015; Hirshleifer et al., 2011). To test this conjecture, we generate an arbitrage index to measure the arbitrage costs comprehensively. The index involves four variables that capture different dimensions of restrictions on arbitrage. The first variable is idiosyncratic volatility, which is deemed as a holding cost forcing arbitrageurs to take limited positions in mispriced stocks. The second variable is the Amihud illiquidity measure, used to capture the transaction cost. The third variable is institutional ownership level, used to measure the cost of short selling. Nagel (2005) suggests that when the level of institutional ownership is low, stock loan supply tends to be less available and short selling will be more expensive. Finally, following Zhang (2006) we use analyst report coverage to measure the information uncertainty.[18] To build the arbitrage index, we group sample stocks into deciles based on an ascending sort of their idiosyncratic volatility and illiquidity, since an increase in these variables indicates a rise in arbitrage costs. We also group stocks into deciles based on a descending sort of their percentage institutional ownership and analyst report coverage, since a reduction in these variables indicates a rise in arbitrage costs. We assign each stock four scores corresponding to the ranks of the four decile groups to which the stock belongs and calculate the arbitrage index (AI) as the sum of the four rank scores. The arbitrage index ranges between 4 and 40, and higher values of the index indicate tighter restrictions on arbitrage.

Each month, we sort negative-β^{FXV} stocks into AI and β^{FXV} quintiles independently. Table 6 provides the risk-adjusted return (α_{FFC6}) for each of the 25 resulting intersection value-weighted portfolios. For the lowest arbitrage index group (AI1), the α_{FFC6} spread between the extreme β^{FXV} quintiles is negative and statistically insignificant; −0.13 % per month (*t*-stat. = −0.38). As the arbitrage index increases, or in other words, as arbitrage restrictions tighten, the α_{FFC6} spread shifts to positive and becomes larger in magnitude. For the highest arbitrage index group (AI5), the α_{FFC6} on the long-short portfolio that buys stocks with almost zero β^{FXV} (quintile 5) and sells stocks with the lowest values of β^{FXV} (quintile 1) is significantly positive, with a value of 0.84 % per month and *t*-statistic of 2.35. The difference in risk-adjusted returns between the long-short portfolios within groups AI5 and AI1 is 0.97 % per month and statistically significant with a *t*-statistic of 2.16. Collectively, these results confirm the prediction that the anomaly for negative β^{FXV} is much stronger for stocks with high arbitrage costs.

We also expect that for overpriced stocks, i.e., stocks with the lowest values of β^{FXV}, those with higher arbitrage costs should be even more overpriced and harder to revert to fair value, and thus there should be a negative relation between arbitrage costs and expected returns. On the other hand, stocks with almost zero β^{FXV} are generally less likely to be mispriced. Hence, for this part of stocks, their expected returns should not change significantly with the increase of arbitrage costs. To test this conjecture, Table 6 also presents the

[18] Analyst report coverage is the number of analyst reports that have tracked a firm over the past year.

Table 7
Robustness tests. This table examines the robustness of the inverted U-shaped relation between FXV-beta and future stock returns. In Panel A, we test if our findings are sensitive to alternative measures of β^{FXV} by running Fama-MacBeth regressions of one-month-ahead excess returns on β^{FXV+} (β^{FXV-}) generated by alternative β^{FXV} measures. In specifications (1) to (4), the β^{FXV} measure is estimated based on alternative factor models: Model 1: $R_{i,t} - R_{ft} = \alpha_i + \beta_{1i}MKT\_FF_t + \beta_{2i}SMB\_FF_t + \beta_{3i}HML_t + \beta_{4i}UMD_t + \beta_{5i}RMW_t + \beta_{6i}CMA_t + \beta_i^{FXV}\Delta Vol_t + \varepsilon_{i,t}$; Model 2: $R_{i,t} - R_{ft} = \alpha_i + \beta_{1i}(R_{wm,t} - R_{ft}) + \beta_{2i}SMB_t + \beta_{3i}VMG_t + \beta_{4i}PMO_t + \beta_i^{FXV}\Delta Vol_t + \varepsilon_{i,t}$. In specifications (5) and (6), the β^{FXV} measure is estimated using the BIS RMB index. In specifications (7) to (10), the β^{FXV} measure is estimated based on Eq. (1) and rolling windows of alternative widths (30 days and 120 days). In specifications (11) and (12), the β^{FXV} measure is estimated using an alternative measure of exchange rate volatility, i.e., the standard deviation of the daily log returns on the RMB index over the past month. In Panel B, we test if our findings are robust in subsamples. We separate the full sample into the following three subperiods and run Fama-MacBeth regressions of future excess returns on lagged β^{FXV+}(β^{FXV-}) over the three subperiods separately: 1) 2006.01–2008.06 and 2010.11–2015.07, when China employs a less market-driven de-pegged exchange rate system; 2) 2008.07–2010.10, when China adopts a fixed exchange rate system pegged to the US dollar; 3) 2015.08–2020.12, when China implements a more market-driven de-pegged exchange rate system. R^2_{adj} is the average adjusted R-squared statistic. $\bar{n}$ is the average number of observations available per month. T is the number of months available in the regression. The sample period spans from January 2006 to December 2020. Newey-West adjusted t-statistics are in parentheses.

Panel A: Alternative measures of β^{FXV}

	Model 1		Model 2		BIS RMB index	
	(1)β^{FXV+}	(2)β^{FXV-}	(3)β^{FXV+}	(4)β^{FXV-}	(5)β^{FXV+}	(6)β^{FXV-}
Estimate	−1.17	0.96	−1.24	1.07	−0.76	0.80
	(−2.66)	(1.82)	(−3.19)	(2.05)	(−2.24)	(2.45)
R^2_{adj}[%]	0.45	0.41	0.46	0.49	0.36	0.31
	30-day rolling window		120-day rolling window		Standard deviation	
	(7)β^{FXV+}	(8)β^{FXV-}	(9)β^{FXV+}	(10)β^{FXV-}	(11)β^{FXV+}	(12)β^{FXV-}
Estimate	−1.03	0.79	−1.35	0.58	−1.94	1.56
	(−6.87)	(2.64)	(−3.18)	(1.22)	(−2.68)	(1.90)
R^2_{adj}[%]	0.48	0.52	0.39	0.44	0.43	0.52

Panel B: Sample period division

	Subperiod 1		Subperiod 2		Subperiod 3	
	(1)β^{FXV+}	(2)β^{FXV-}	(3)β^{FXV+}	(4)β^{FXV-}	(5)β^{FXV+}	(6)β^{FXV-}
Estimate	−1.07	0.82	−2.30	2.21	−1.66	1.25
	(−2.35)	(1.75)	(−1.70)	(1.08)	(−2.23)	(1.59)
R^2_{adj}[%]	0.48	0.54	0.36	0.40	0.44	0.47
$\bar{n}$	1312	1312	1172	1172	2150	2150
T	87	87	28	28	65	65

α_{FFC6} difference between the extreme AI quintiles (AI5 −AI1) for each β^{FXV} group. As expected, there is no significant relationship between stock returns and arbitrage costs in the almost zero-β^{FXV} group (quintile 5). However, for stocks in the lowest-β^{FXV} group (quintile 1), the α_{FFC6} difference between AI5 and AI1 is negative and highly significant, which supports our conjecture.

In summary, the analysis of arbitrage costs provides additional evidence for the mispricing explanation for the underperformance of low-β^{FXV} stocks.

6. Robustness tests

In this section, we conduct a series of robustness tests for the inverted U-shaped relation between FXV-beta and future stock returns.

6.1. Alternative measures of FXV-beta

First, we examine whether our findings are sensitive to alternative measures of β^{FXV}. To this end, we run Fama-MacBeth regressions of one-month-ahead excess returns on β^{FXV+} (β^{FXV-}) generated based on alternative measures of β^{FXV}. The results are summarized in Panel A of Table 7.

In our main analysis, we estimate the β^{FXV} coefficient for each stock based on the CH4 model. We now use the FFC6 model (Model 1) and the international CAPM model augmented with the size, earnings-price, and turnover factors of Liu et al. (2019) (Model 2) to

Table A1
Variable definition.

Variable	Symbol	Definition
Market beta	β^{MKT}	Market beta is estimated from the CAPM regression at the end of each month using daily return data for the past year (250 trading days). We require at least 200 daily returns available in the estimation window.
Downside beta	β^{Down}	Downside beta is calculated in the same way as market beta, expect that it is estimated only using return observations on the days when the market's excess return is below the average market excess return over the past year.
Market value	*Size*	Market value is the log of the market capitalization measured by price times number of outstanding A-shares at the end of each month.
Book-to-market ratio	*BM*	Book-to-market ratio is book equity divided by market capitalization at the end of each month.
Momentum	*Mom*	Momentum is the cumulative stock return for the period beginning twelve months before and ending one month before the portfolio formation month (a total of eleven months). We require a minimum of nine available monthly returns over the 11-month measurement period.
Reversal	*Rev*	Reversal is the stock return over the previous month.
Co-skewness	*CoSkew*	Co-skewness is calculated nonparametrically at the end of each month using daily return data for the past year (250 trading days). We require at least 200 daily returns available in the estimation window. See Appendix B of Chabi-Yo et al. (2018) for the calculation formula.
Co-kurtosis	*CoKurt*	Co-kurtosis is calculated nonparametrically at the end of each month using daily return data for the past year (250 trading days). We require at least 200 daily returns available in the estimation window. See Appendix B of Chabi-Yo et al. (2018) for the calculation formula.
Illiquidity	*Illiq*	Illiquidity is the average of the ratios of absolute daily stock returns to daily dollar trading volumes within a month. We require a minimum of 15 daily observations available in each month when calculating *Illiq*.
Idiosyncratic volatility	*IdioVol*	Idiosyncratic volatility is estimated using the residual standard error from a regression of daily excess stock returns on the daily returns of the Fama-French (1993) three factors over the past year (250 trading days). We require at least 200 daily observations available in the estimation window.
Idiosyncratic skewness	*IdioSkew*	Idiosyncratic skewness is estimated using the residual skewness from a regression of daily excess stock returns on the daily returns of the Fama-French (1993) three factors over the past year (250 trading days). We require at least 200 daily observations available in the estimation window.
Value-at-risk	*VaR*	Value-at-risk is the 5 % quantile of the empirical distribution of returns over the past 250 days. We require at least 200 daily observations available in the estimation window.

generate two alternative measures of β^{FXV} and test whether these measures are equally capable of predicting future cross-sectional returns.[19] Specifications (1) to (4) of Table 7, Panel A, show that our main findings still hold after replacing the CH4 model with other models. When we estimate β^{FXV} using Models 1 and 2, the slope coefficient on β^{FXV+} remains significantly negative and that on β^{FXV-} remains significantly positive.

We also estimate stock exposures to the RMB exchange rate volatility based on the BIS RMB index published by the Bank for International Settlements (BIS). The BIS basket consists of 64 currencies. The BIS RMB index is computed as the geometric weighted mean of the bilateral exchange rates between the RMB and foreign currencies. The weights are derived from manufacturing trade flows, taking into account both direct bilateral trade and third-party market competition. Specifications (5) and (6) show that our findings remain stable when estimating β^{FXV} using the BIS RMB index. However, compared to that in Column 1 of Table 3, Panel A, the premium for positive FXV-betas in specification (5) is much lower in magnitude and weaker in statistical significance. For this result, a plausible explanation is that the BIS basket includes too many non-mainstream international settlement currencies, whose exchange rate against the RMB has little impact on the Chinese stock market, so investors have a relatively low hedging demand for the volatility of the BIS RMB index.

In specifications (7) to (10), we demonstrate that our main results do not hinge upon the width of the rolling window used to estimate β^{FXV}. When Eq. (1) is estimated over a 30-day or 120-day rolling window (instead of a 60-day rolling window), there remains a significantly negative relation between β^{FXV+} and future stock returns and a positive relation between β^{FXV-} and future stock returns.

We also redefine the volatility of the RMB exchange rate on a given day as the standard deviation of the daily log returns on the RMB index over the past month and use this new volatility measure to estimate β^{FXV} for each stock following the methodology in Section 3. The regression results of specifications (11) and (12) show that the inverted U-shaped relation between β^{FXV} and future returns remains robust after we change the measure of exchange rate volatility.

6.2. Sample period division

Next, we test the robustness of our findings in subsamples. While our sample period 2006–2020 is after the de-pegging of the RMB from the US dollar in July 2005, there is a period—from July 2008 to October 2010—when the RMB exchange rate against the US dollar was basically fixed in response to the global financial crisis. After the crisis, the RMB was once again de-pegged from the US

[19] Model 1: $R_{i,t} - R_{ft} = \alpha_i + \beta_{1i}MKT\_FF_t + \beta_{2i}SMB\_FF_t + \beta_{3i}HML_t + \beta_{4i}UMD_t + \beta_{5i}RMW_t + \beta_{6i}CMA_t + \beta_i^{FXV}\Delta Vol_t + \varepsilon_{i,t}$; Model 2: $R_{i,t} - R_{ft} = \alpha_i + \beta_{1i}(R_{wm,t} - R_{ft}) + \beta_{2i}SMB_t + \beta_{3i}VMG_t + \beta_{4i}PMO_t + \beta_i^{FXV}\Delta Vol_t + \varepsilon_{i,t}$. *MKT_FF*, *SMB_FF*, and *HML* is the market, size, and value factors of Fama and French (1993). *UMD* is the momentum factor of Carhart (1997). *CMA* and *RMW* is the investment and profitability factors of Fama and French (2015). R_{wm} is the return on the global stock market composite index, which is proxied by the MSCI world index.

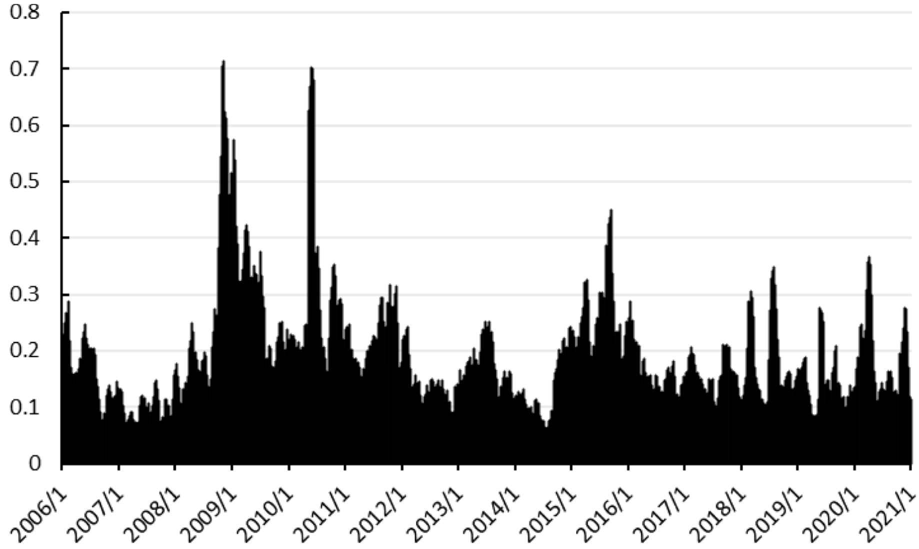

Fig. A1. Daily volatility of RMB effective exchange rate.

dollar. In addition, as mentioned in the institutional background (Section 2), in August 2015, the People's Bank of China implemented a more in-depth reform to the formation mechanism of the central parity rate of the RMB against the US dollar, and since then the degree of marketization and tow-way volatility of the RMB exchange rate have been further increased. Hence, we divide our full sample into the following three subperiods for testing the robustness of our findings under different RMB exchange rate regimes: 1) 2006.01–2008.06 and 2010.11–2015.07, when China employs a less market-driven de-pegged exchange rate system; 2) 2008.07–2010.10, when China adopts a fixed exchange rate system pegged to the US dollar; 3) 2015.08–2020.12, when China implements a more market-driven de-pegged exchange rate system.

We run monthly cross-sectional regressions of future excess returns on lagged β^{FXV+} (β^{FXV-}) over the three subperiods separately. Panel B of Table 7 reports the time-series averages of the slope estimates from the regressions. We find that in subperiods 1 and 3, when the RMB is de-pegged from the US dollar, the slope coefficients on β^{FXV+} are -1.07 (t-stat. $= -2.35$) and -1.66 (t-stat. $= -2.23$), respectively, both of which are highly significantly negative. In subperiod 2, when the RMB is pegged to the US dollar, the slope coefficient on β^{FXV+} turns out to be -2.30 (t-stat. $= -1.70$), which is much higher in absolute value but weaker in statistical significance. We attribute this result to the large variation in the monthly slope coefficients of β^{FXV+} between July 2008 and October 2010 (see Fig. 2).[20] Overall, these results suggest that the premium for positive FXV-betas appears to be more significant during periods of the RMB de-pegging from the US dollar. We also find that in all subperiods, there is a positive slope coefficient on β^{FXV-}, which once again highlights the inverted U-shaped relation between FXV-beta and future returns.

7. Conclusion

This paper investigates the impact of RMB exchange rate volatility on the cross-sectional pricing of Chinese A-share stocks. RMB exchange rate volatility is defined as the mean of the absolute daily log returns on the RMB index over the past month. We estimate stock exposure to the RMB exchange rate volatility and find an inverted U-shaped (nonlinear) relation between the resulting FXV-betas (i.e., β^{FXV}) and future stock returns, that is, both stocks with high β^{FXV} and those with low β^{FXV} yield lower future returns.

The ICAPM theory of Merton (1973) suggests that the underperformance of stocks with high β^{FXV} is due to intertemporal hedging demand. More specifically, investors are willing to pay higher prices and accept lower returns to hold high-β^{FXV} stocks to hedge against the deterioration in investment opportunities caused by heightened exchange rate volatility, as the returns of these stocks tend to increase with higher volatility. We provide evidence for the intertemporal hedging demand explanation in two ways. First, our analyses based on bivariate portfolio sorts and multivariate Fama-MacBeth regressions show that the negative relation between positive β^{FXV} and future returns cannot be explained by other firm characteristics and risk factors. Second, we show that the premium for

[20] As shown in Fig. 2, the average value of -2.30 for the slope coefficient on β^{FXV+} in subperiod 2 is primarily driven by several extremely negative outliers. Although the RMB exchange rate against the US dollar is basically fixed from July 2008 to October 2010, the RMB exchange rates against other currencies (including Euro, British pound, Korean won, Japanese yen, and Singapore dollar) still exhibit a high level of volatility due to the impact of the global financial crisis (see Fig. A2 of the Appendix). As a result, the RMB index in general also exhibits large fluctuations during this period, resulting in some extremely negative estimates of the monthly slope coefficient on β^{FXV+}. Additionally, we argue that the small number of months involved in the regression (only 28 months) is also an important factor contributing to the large variance of the monthly slope estimates during subperiod 2.

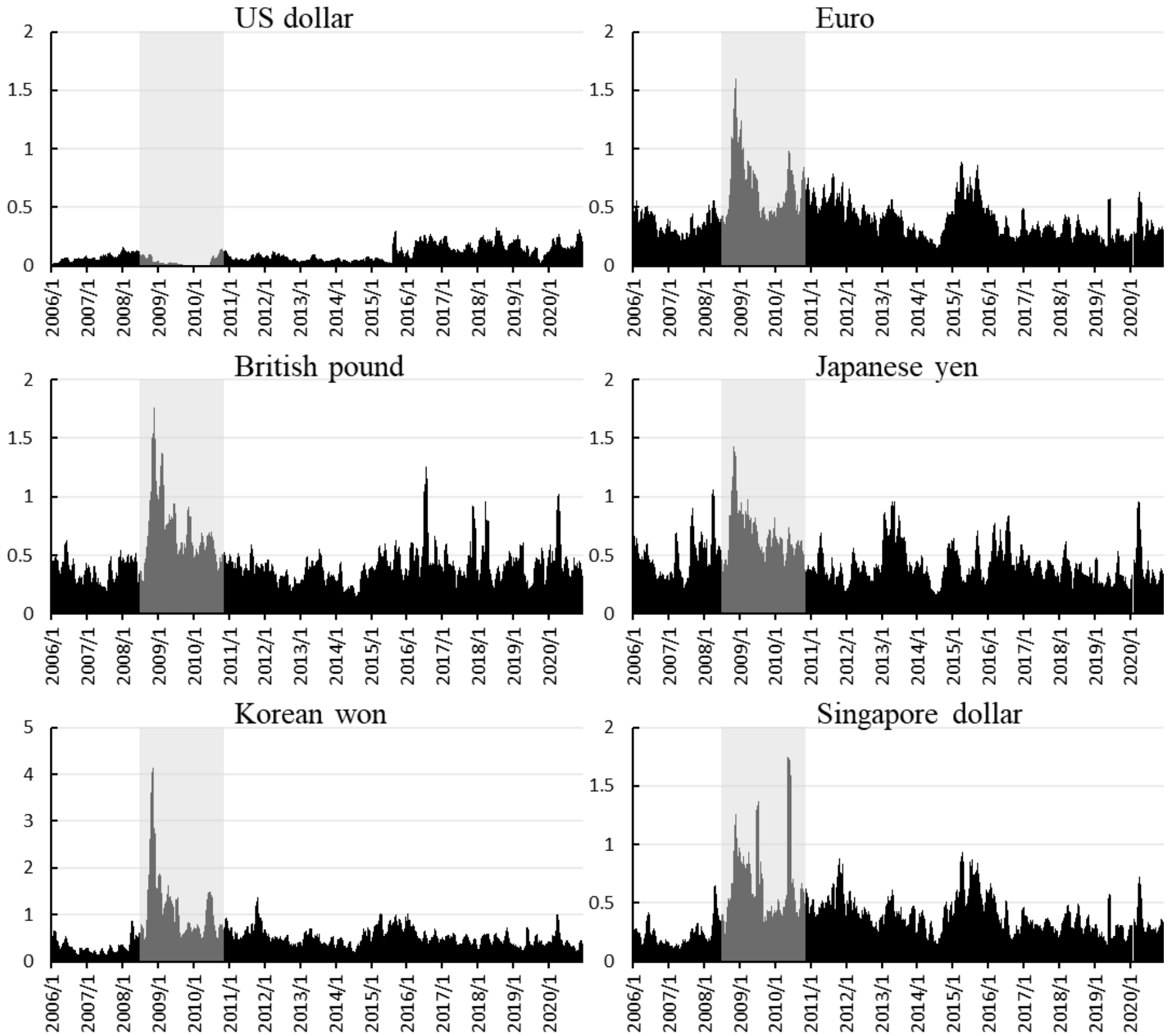

Fig. A2. Daily volatility of bilateral exchange rates.

positive β^{FXV} is time-varying and state-dependent; it becomes higher in magnitude and more statistically significant during periods of high exchange rate volatility, when investors are expected to show stronger hedging demand. We argue that the underperformance of high-β^{FXV} stocks is primarily dominated by rational institutional investors, as they are more capable and motivated to hedge foreign exchange risk than less rational individual investors.

As for stocks with low β^{FXV}, which suffer losses as exchange rate volatility increases, theory predicts that risk-averse investors would pay relatively low prices for these stocks and demand higher returns as compensation. However, our results reveal the opposite of this prediction. We find that low-β^{FXV} stocks produce significantly lower future returns only when they exhibit strong lottery characteristics. Moreover, the anomaly for negative β^{FXV} is more pronounced for stocks with higher levels of individual ownership and higher arbitrage costs. These findings suggest that the underperformance of low-β^{FXV} stocks could be the result of mispricing due to individual investors' lottery demand.

CRediT authorship contribution statement

Tongshuai Qiao: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft. **Wenjie Ding:** Conceptualization, Investigation, Funding acquisition, Writing – original draft, Writing – review & editing. **Liyan Han:** Conceptualization, Data curation, Funding acquisition. **Donghui Li:** Conceptualization, Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

Fig. A1 presents the daily volatility of the RMB effective exchange rate, calculated as the mean of the absolute daily log returns on the RMB index of Wu et al. (2019) over the past 20 days. The sample period is from January 2006 to December 2020.

Fig. A2 presents the daily volatility of the RMB exchange rates against the US dollar, Euro, British pound, Japanese yen, Korean won, and Singapore dollar. The volatility on a given day is calculated as the mean of the absolute daily log returns of the bilateral exchange rates over the past 20 days. The sample period is from January 2006 to December 2020. The shaded area represents the period from July 2008 to October 2010.

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