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Specification tests of international asset pricing models

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Abstract

This study evaluates the cross-sectional pricing performances of several international asset pricing models. The comparison metric is the Hansen and Jagannathan [Hansen, L., Jagannathan, R., 1997. Assessing specification errors in stochastic discount factor models. Journal of Finance 52, 557–590] distance, and the models are required to price size and book-to-market portfolios from the US, the UK and Japan. When betas and risk premiums are constant over business cycles, none of the models can pass the specification test. By allowing time-varying betas and risk premiums in conditional models, most models can pass the specification test. This is because these models capture the assets' different sensitivities to the time-varying risk premiums, which explain most of the book-to-market return spread. The Fama–French factors are redundant in conditional models. Finally, exchange risk premiums account for a significant part of the excess returns on international assets, and the conditional International CAPM with exchange risk performs the best. The market integration hypothesis is also supported.

JEL classification: G12; G15; F36; E32

Keywords: International asset pricing; Market integration hypothesis; Time-varying betas; Exchange risk

1. Introduction

Since the late 1970s, the major developed countries have gradually rescinded capital controls and opened their domestic markets to foreign investors. As a result, domestic investors are

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facing a larger investment opportunity set, which includes both domestic assets and foreign assets. One natural question to ask is: how should we price international assets?

This study tries to answer this question by evaluating alternative international asset pricing models. I focus on pricing cross-sectional return spreads by using the size and book-to-market (B/M hereafter) portfolios from the US, the UK and Japan as the base assets. Because these base assets display large cross-sectional return spreads, they are challenging for every asset pricing model, which makes the specification tests powerful.[1] Most previous studies of international asset pricing choose national market indices as the base assets. However, the national index can hardly cover the complete investment opportunity set within a country. As investors have direct access to individual assets, it is more relevant to conduct asset pricing tests at the individual portfolio level.

If the world market is integrated, then assets with the same risk characteristics should receive the same prices, irrespective of their nationalities. This requires that only global risk factors are priced for international assets, and they receive the same prices across countries. Every international model assumes that the world capital market is integrated.[2] Thus, the international model is a joint hypothesis of the model's risk specification and the underlying market integration hypothesis. The simplest international model is the International single-beta CAPM in Grauer et al. (1976). By assuming Purchasing Power Parity (PPP), the model treats global market risk as the only relevant risk. When PPP does not hold, investors using different currencies for consumption face different investment opportunity sets, and exchange risk becomes priced, as in Solnik (1974) and Adler and Dumas (1983).[3] However, Fama and French (1998) argue that the global market risk is unable to capture the cross-sectional return spreads among portfolios sorted by B/M ratio in the global market. Thus, they propose an alternative multi-factor model by adding in empirically motivated factors.

I use the Hansen and Jagannathan (1997) distance measure (hereafter HJ-distance) to evaluate these models. Given one asset pricing model, the magnitude of HJ-distance is the maximum pricing error achievable for a normalized portfolio. This maximum error can be directly compared across models as a mispricing measure. The best model should have the smallest HJ-distance. Moreover, if the model is correctly specified, this maximum error should be zero. Since the distribution of the HJ-distance under correct asset pricing is known, we can examine the validity of the model by testing whether its HJ-distance equals zero. There are several alternative approaches, such as the optimal GMM and the regression method. I prefer the HJ-distance approach for its easy interpretation and its direct comparability across models, but I also use the optimal GMM to examine the robustness of the HJ-distance approach.

I first examine the unconditional implication of the models, where the individual asset's betas and the risk premiums are assumed to be constant over business cycles. But this assumption may not be realistic. For instance, financially constrained firms may be more sensitive to

[1] By using the size and B/M portfolios, there is a concern that the results would be biased toward the Fama–French factor model. But the empirical results demonstrate that this is not true.

[2] Studies using national market indices as basic assets cannot reject the market integration hypothesis (see Gultekin et al., 1989; Bekaert and Harvey, 1995; Dumas and Solnik, 1995; and De Santis and Gerard, 1998). Other studies using individual assets or individual portfolios give mixed results for market integration hypothesis (see Heston et al., 1995). By using individual portfolios as the base assets, my specification test provides another chance to examine the market integration hypothesis.

[3] Empirically, Dumas and Solnik (1995) report that exchange risks are important for international asset pricing, and De Santis and Gerard (1998) report that exchange risks comprise a significant part of national indices' returns.

changes in macroeconomic conditions, especially during recessions. Thus, they may have time-varying betas. Similarly, risk premiums may also be time varying. For instance, the market risk premium should be higher at economic downturns to compensate for the adverse risk exposure. I incorporate time variation in betas and risk premiums by assuming that the model holds conditionally. The conditional models include time-varying risk premiums as an additional factor. Since the time variation in risk premiums should be related to business cycles, I proxy for the time-varying risk premiums with business cycle variables. I include two business cycle variables in this article, the Hodrick and Prescott (1997) filtered global industrial production, and the HP-filtered US short interest rate.

The main results are as follows. None of the unconditional models pass the HJ-distance test, while most of the conditional models are accepted as correct models. The time-varying risk premiums proxied by the two business cycle variables help to capture most of the B/M spreads, especially when using the HP-filtered industrial production. The Fama–French factors are redundant in the presence of business cycle variables. Finally, exchange risk premiums contribute significantly to the excess returns on international assets, and the conditional International CAPM with exchange risk performs the best among all models. The market integration hypothesis is also supported.

One closely related work is Fama and French's (1998) paper, which evaluates international asset pricing models by using them to price the international B/M effect. Fama and French assume that there is no exchange risk and they only test unconditional models. My study relaxes these restrictions to avoid possible model misspecification. This article also explores the relation between the Fama and French factors, the exchange risk factors, and the business cycle variables, and how they affect individual portfolio returns. Moreover, Fama and French construct the B/M portfolios from MSCI data, which only cover large firms in every national market. This study uses DataStream data, which cover many small firms. This allows me to investigate the global size effect and to construct portfolios along both size dimension and B/M dimension.

The paper is organized as follows. The next section contains a brief description of the methodology. Section 2 describes the data. Section 3 provides the empirical asset pricing results on international assets. Section 4 discusses whether country-specific factors are priced in an integrated market. Section 6 concludes.

2. Methodology

2.1. Market integration hypothesis

Assume there are L countries, and each has its own currency. Country i has N_i assets, $i=1,\ldots,L$. The dollar denominated return vector[4] for country i is denoted R_i. Define $N=\sum_{i=1}^{L} N_i$, and $R=\left[R_1', R_2', \ldots, R_L'\right]'$ is the $N\times 1$ return vector of all assets in the world.

The world market is completely integrated if assets with the same risk characteristics have identical expected returns, irrespective of their nationalities. If there are no arbitrage opportunities in the world market, the market integration hypothesis implies that there exists a set,

[4] The use of different denomination currency does not affect the validity of market integration hypothesis or HJ-distance approach. More details are covered in Appendix A.

M_{t+1}, of correct global pricing kernels m_{t+1}, which can price every asset return $R_{j,t+1}$ in the world market. Unconditionally, that is

$$E\left(m_{t+1}R_{j,t+1}\right) = p_j, \quad \forall t > 0, \quad \forall j = 1,\ldots,N, \text{ and } \forall m_{t+1} \in M_{t+1}, \tag{1}$$

where p_j is the price for return $R_{j,t+1}$ at time t. If $R_{j,t+1}$ is the gross return for a portfolio, then $p_j = 1$; if $R_{j,t+1}$ is the excess return for a portfolio, then $p_j = 0$.

Since the correct global pricing kernels, m_{t+1}, are not observable, every international asset pricing model provides a pricing proxy, y_{t+1}, for m_{t+1}. This article only examines linear factor models because of their tractability. The linear pricing proxy y_{t+1} can be written as

$$y_{t+1} = b'F_{t+1} = b_0 + b_1'f_{t+1}, \tag{2}$$

where $F_{t+1} = [1,\ f_{t+1}]'$ is the $(K+1)\times 1$ global factor vector, and $b = \left[b_0, b_1'\right]'$ is the $(K+1)\times 1$ global factor price vector. The specification of the global pricing proxy implies that only global factors, F, are priced for assets in the world market, and these global factors receive the same prices, b, across different countries.

The market integration hypothesis is supported if the set M is not empty, that is to say, there exists at least one global pricing proxy y that can pass the HJ-distance specification test, as described below.[5] For ease of presentation, I will drop the time subscript.

2.2. HJ-distance

If the international model's risk specification is correct, then $y \in M$, otherwise $y \notin M$. Thus, for a false model there is a strictly positive distance between y and M. Hansen and Jagannathan (1997) define the distance, or HJ-distance, as

$$\delta = \min_{m \in L^2} \|y - m\|, \quad \text{where } E(mR) = p, \tag{3}$$

and $\|x\| = \sqrt{E(x^2)}$ is the norm of x.[6] They solve Eq. (3) to find $y - \tilde{m} = \tilde{\lambda}'R$, where $\tilde{m}$ is the solution to Eq. (3), and the multiplier is

$$\tilde{\lambda} = E(RR')^{-1}E(yR - p). \tag{4}$$

One can think of $y - \tilde{m}$ as the minimal adjustment to y to make it a correct pricing kernel. Thus, the HJ-distance is

$$\delta = \|y - \tilde{m}\| = \|\tilde{\lambda}'R\| = \left[E(yR - p)'E(RR')^{-1}E(yR - p)\right]^{1/2}. \tag{5}$$

There are two intuitive interpretations for the δ measure. First, δ is the maximum pricing error for the set of asset payoffs with norm equal to one. That is, with base assets' returns R, the maximum pricing error δ is achieved by a portfolio of those assets with weights γ, where $\gamma = (1/\delta)\tilde{\lambda}$ and $\|\gamma'R\| = 1$. To take the biggest advantage of the mispricing of each model, the

[5] On the other hand, if the world market is not completely integrated (segmentation or partial segmentation), the M should be empty, and no global pricing proxy y should be able to pass the specification test.

[6] Hansen and Jagannathan (1997) also consider a distance measure in which m is required to be strictly positive. If the problem is solved without the constraint and $m_{t+1} > 0$ for all t, the two solutions coincide. In their empirical analysis, Hansen and Jagannathan (1997) find that this additional restriction does not make a big difference.

investors should invest in this maximum error portfolio. Second, HJ-distance is approximately the maximum difference in Sharpe ratios defined by m and y, for any portfolios constructed from the base assets' returns R. Suppose we have a portfolio constructed from the N assets with payoff ξ. Let $E^y(\xi)$ be the expected value of the payoff ξ predicted by the pricing proxy y, and let $E(\xi)$ be the expected value predicted by a correct pricing kernel m. Then we have

$$\frac{\delta}{E(m)} = \frac{\delta}{E(y)} = \max_{\xi} \frac{|E^y(\xi) - E(\xi)|}{\sigma(\xi)}. \tag{6}$$

The right-hand side is the maximum pricing error per unit of standard deviation, i.e., the maximum difference between the two Sharpe ratios, $(E^y(\xi))/(\sigma(\xi))$ and $(E(\xi))/(\sigma(\xi))$.[7]

From Eq. (5), δ is the product of three components. The first and third components are model errors, $g = E(yR - p)$, which measure the difference in prices assigned by the true pricing kernel and our pricing proxy y.[8] The second component is a weighting matrix. This "sandwich" structure implies that the HJ-distance methodology is a typical GMM approach. This approach provides inferences in three ways. First, δ, as a mispricing measure, can be directly compared across models. Second, if the candidate model is correctly specified, then δ should not be significantly different from zero. Thus, the HJ-distance provides a specification test.[9] Third, estimates of risk prices b and model errors g provide diagnostics on significance of global risk factors, and cross-sectional performance of different models. Detailed discussion on estimation and comparison with other methods are presented in Appendix B.

The HJ-distance methodology, like other GMM methodologies, has two caveats. First, the statistical inference is affected by the sample size. Ahn and Gadarowski (2004) find that, with a small sample size, the expected value of the HJ-distance for a correct model can be quite large instead of zero, and the HJ-distance tests over-rejects. To adjust for the small sample bias, I use the Monte Carlo method to calculate the empirical distributions of the HJ-distance with small sample sizes. Details are covered in Appendix C. Second, the HJ-distance test and other GMM tests assume the parameters are stationary, while parameter stability is not guaranteed in any model. I use the supLM test of Andrews (1993) to test whether the parameters are stable.[10]

2.3. Unconditional models and conditional models

Since the focus of this paper is to price the cross-sectional return spreads, I first investigate the pricing implication if the models hold unconditionally, as in Eq. (1). Under the null hypothesis of $y \in M$, we have

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[7] For this interpretation to hold, we need to assume $E(m) = E(y) = (R^0)^{-1}$, i.e., the pricing proxy y can correctly price the riskfree rate R^0. My estimation results indicate that $E(y)$ for all models is around 0.996, which implies a reasonable value for R^0 of 1.004 per month.

[8] I also define average return errors or Jensen's α as $\alpha = \overline{R} - E(R)$, which is equivalent to $R^0 g$. Since the estimated R^0 differs slightly across models, g and α do not really provide identical information. But since R^0 is very close to one, the Jensen's α is not very different from g. To avoid confusion, this paper only uses g to estimate parameters, and to compare models' performances.

[9] As in Jagannathan and Wang (1996), the test statistic, $T\delta^2$ is asymptotically distributed as a weighted sum of $(n-k)$ $\chi^2(1)$ statistics under the null hypothesis.

[10] The LM statistics are evaluated at 5% increments between 25% and 75% of the sample, and the largest is the supLM statistic. The distribution of supLM statistic is obtained from Monte Carlo experiment over large samples, but no research has been done on its finite sample performance.

$$E(R_j) = \frac{p_j - \mathrm{cov}(y, R_j)}{E(y)}, \quad j = 1, \ldots, N.$$

Since $E(y) = (1/R^0)$ and $y = b'F$, the unconditional model has an equivalent representation in terms of multivariate betas and beta risk premiums,

$$E(R_j) = R^0 p_j + \beta_j' \Lambda, \tag{7}$$

where $\beta_j = \mathrm{cov}(f, f')^{-1}\,\mathrm{cov}(f, R_j')$, and $\Lambda = -R^0 \mathrm{cov}(f, f') b_1$. In Eq. (7), the β_j's are the factor loadings (the projections of the returns onto the factors), which measure asset j's average sensitivities to the risk factors; the Λ's are the associated beta risk premiums, which measure how much return should be awarded for bearing the risks. Since the Λ's are the same for all assets, the cross-sectional return spreads should be reflected in the individual asset's factor loadings, β_j.[11] The expected return of asset j can be disaggregated into rewards for its covariances with different sources of risks, $\Lambda_k \beta_{k,j}$, $k = 1, \ldots, K$. Each $\Lambda_k \beta_{k,j}$ reflects the magnitude of the kth risk's impact on the asset j's expected return and is referred to as the risk adjustment for the kth risk.

When we examine the unconditional models, we assume the β_j's and Λ's are constant over the business cycle, as in Eq. (7). However, as discussed in numerous articles, both β and Λ are more likely to be time varying.[12] Next, I allow time-varying betas and time-varying risk premiums by assuming the model holds conditionally.

Similar to Eq. (1), if based on the information set at time t (denoted by Φ_t), m_{t+1} can price every asset correctly, we have

$$E_t(m_{t+1} R_{j,t+1}) = p_j, \quad \forall t > 0, \ \forall j = 1, \ldots, N, \text{ and } \forall m_{t+1} \in M_{t+1}. \tag{8}$$

Under the null hypothesis of $y_{t+1} \in M_{t+1}$,

$$E_t(R_{j,t+1}) = \frac{p_j - \mathrm{cov}_t(y_{t+1}, R_{j,t+1})}{E_t(y_{t+1})}.$$

Since $E_t(y_{t+1}) = (1/R^0_{t+1})(\in \Phi_t)$ and $y_{t+1} = b'F_{t+1}$, this is equivalent to

$$E_t(R_{j,t+1}) = R^0_{t+1} p_j - \beta_{j,t}' \Lambda_t, \tag{9}$$

where the vector $\beta_{j,t} = \mathrm{cov}_t(f_{t+1}, f'_{t+1})^{-1} \mathrm{cov}_t(f_{t+1}, R'_{j,t+1})$ are the time-varying betas, and the vector $\Lambda_t = -R^0_{t+1} \mathrm{cov}_t(f_{t+1}, f'_{t+1}) b_1$ are the associated time-varying risk premiums.

[11] All parameters can be calculated once b is known. To answer whether the kth factor significantly influences the expected returns on a particular set of portfolios, we must assess whether the corresponding Λ_k is significantly different from zero. Note $\Lambda_k = 0$ does not mean $b_{1,k=0}$, and vice versa. Only when $\mathrm{cov}(f, f')$ is diagonal are the two statements equivalent. The derivation and proof of this statement can be found in Cochrane (1996).

[12] As in Jagannathan and Wang (1996), financially constrained firms are more sensitive to changes in macroeconomic conditions, especially during recessions. Thus, they may have time-varying betas. Similarly, the risk premiums may also be time varying. For instance, the market risk premium should be higher at economic downturns to compensate for the adverse risk exposure.

However, we cannot directly test Eq. (9), because the HJ-distance measure is an unconditional measure. Therefore, we can only test the unconditional implications of Eq. (9). Jagannathan and Wang (1996) elaborate that after simplification, the unconditional expected returns are linear functions of two kinds of betas, the average risk betas, β_j, and the premium betas, $\beta_{j,\Lambda}$. Hence,

$$E\left(R_j\right) = R^0 p + \beta_j' \Lambda + \beta_{j,\Lambda}' \Lambda^*,$$

where the premium betas, $\beta_{j,\Lambda} = \mathrm{cov}\left(\Lambda_t, \Lambda_t'\right)^{-1} \mathrm{cov}(\Lambda_t, R_{j,t+1}')$, measure the individual return j's sensitivities to the time-varying risk premiums, and Λ^*'s represent the corresponding beta risk premiums. Thus, by allowing the betas and the beta risk premiums to be time varying, we introduce a new term, the beta-sensitivity, into the pricing equation, and this term captures the impact of time variation on asset returns.

Since Λ_t's, the time-varying risk premiums, are not observable, we cannot directly calculate the premium betas, $\beta_{j,\Lambda}$. Since the conditional risk premiums are expected to covary with the business cycle, I approximate Λ_t's by linear functions of z_t, where $z_t \in \Phi_t$ is a business cycle variable. Then the pricing equation changes to

$$E\left(R_j\right) = R^0 p_j + \beta_j' \Lambda + \beta_{j,z} \Lambda_z, \tag{10}$$

with $\beta_{j,z} = \mathrm{var}(z_t)^{-1} \mathrm{cov}(z_t, R_{j,t+1}')$ to be the new premium beta. For the equivalent pricing kernel representation, this amounts to adding the business cycle factor to the original pricing proxy to capture the time variation effect. Thus, the conditional pricing proxies in this article are in the form of

$$y_{t+1} = b' F_{t+1} + b_z z_t.^{13} \tag{11}$$

Conditional models are attractive because unconditional models may not adequately capture time variation in betas and risk premiums. If the conditional model is correctly specified and captures the dynamics in underlying risks, it will outperform the unconditional models. However, by including the business cycle factor, a conditional model uses an additional degree of freedom in the minimization problem and is better able to fit the data. Since the better performance of conditional models may come from the additional degree of freedom, we need to examine both the parameter estimates and the behavior of model errors to identify economically interesting models, in which the conditioning information is significantly priced and the model errors are improved.

[13] Another popular approach to introduce time variation into a pricing proxy is to assume that the factor risk prices $b = \left[b_0, b_1'\right]'$ are time varying, as in Cochrane (1996). The beta-sensitivity approach is consistent with the time-varying risk prices' approach, but it only allows b_0 to be time varying. By restricting b_1 to be constant, I effectively control the geometric expansion in the number of free parameters, because too many free parameters will make the conditional models unstable, the better-fit problem worse and the results hard to interpret.

Table 1
Characteristics of the country samples

	1982	1983	1984	1985	1986	1987	1988	1989	1990	1992	1997
Panel A: Number of firms included in the portfolios for each country											
Japan	70	87	87	670	775	823	837	906	1338	1428	1499
UK	1315	1358	1426	1512	1384	1364	1376	1390	1389	1340	1445
US	3057	3266	3350	3543	3574	3548	3776	3898	3811	3777	5104
Panel B: Country weights from datastream global index (%)											
Japan	25.5	22.1	24.8	26.0	28.4	38.0	48.3	49.6	44.9	32.2	16.8
UK	8.7	7.4	7.1	7.4	8.0	7.6	7.9	7.4	7.4	8.9	9.3
US	48.5	54.9	52.2	51.9	46.0	37.1	28.8	25.5	25.2	33.7	40.4

	1982		1987		1992		1997	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Panel C: Mean and median size (market capitalization, in $ million)								
Japan	1002.5	498.6	1794.1	611.0	1135.8	367.0	1631.1	353.2
UK	107.4	12.2	440.1	56.5	672.3	49.8	932.7	78.6
US	250.9	26.8	573.6	49.6	778.6	63.0	1342.9	124.6
Panel D: Mean and median book-to-market ratio								
Japan	0.6	0.6	0.4	0.4	0.4	0.4	0.6	0.6
UK	1.7	1.4	0.8	0.6	1.0	0.7	0.6	0.5
US	1.1	0.9	0.8	0.6	1.0	0.6	0.6	0.5

Data for Japan and the UK are obtained from DataStream; data for the US are obtained from Compustat and CRSP. Panel A shows the number of firms for each country at the beginning of the year. I present the number for each year before 1990 because the number of firms is relatively unstable during that period. The numbers for the US in Panel A is smaller than that in Table 1 of Fama and French (1998). The reason is that Panel A only reports the number of firms included in the portfolios, not those used in the process of constructing portfolios as in Fama and French (1998). Panel B reports the country weights from DataStream Global Index, which are used later to construct global factors. Panel C shows the mean and median size (market capitalization, price times shares outstanding) of firms included in the size and B/M portfolios in the study. The mean and median are sampled in each June. Panel D shows the mean and median book-to-market ratio of the firms included in the size and B/M portfolios. The mean and median are sampled at the fiscal year end for the US and in each December for the other countries.

3. Data

3.1. Base assets: size and B/M portfolios

This article studies monthly portfolio returns from Japan, the UK, and the US. Data for Japan and the UK are obtained from DataStream.[14] Data for the US are from Compustat and CRSP. The sample period is 1981:07–1997:12, for 198 monthly observations.[15]

Table 1 summarizes the characteristics of my sample. Panel A reports the number of firms included in the portfolios for each country. Compared to Panel A of Fama and French's (1998)

[14] For Japan, DataStream dataset contains firms listed in the two sections of the Tokyo Stock Exchange, which cover more than 85% capitalization of the Japan market. For the UK, DataStream dataset covers the quoted firms, unquoted firms and financial firms. Since DataStream is an UK company, its coverage of UK firms is comprehensive. I also include return data for delisted firms, so the concern on survivorship bias should be alleviated.

[15] The short sample period induces the small sample bias, but it also makes constant integration status more reasonable.

Table 1, my sample has many more firms. For instance, Fama and French's UK annual sample includes 185 firms on average, my annual sample includes about 1400 UK firms on average. Panel B provides country weights calculated from DataStream's Global index. It is evident that Japan's market share declined, while the US market share climbed after 1989. The mean and median firm sizes for each market are provided in Panel C. This study includes more small firms for Japan and the UK than Fama and French (1998) do. For instance, the median firm size for UK companies in Fama and French (1998) is 907 million dollars over 1975–1995, but it is only 78.6 million dollars even in 1997 for my sample. The last panel reports the mean and median B/M ratios.[16] There are some variations in B/M ratios from country to country, and it may be due to the different accounting standards used. For this reason, all portfolios are constructed within their home countries for comparability. Overall, the B/M ratios are not very different from Fama and French's (1998) numbers.

The portfolios are constructed according to Fama and French (1993). The firms within one country are sorted into size and B/M ratio groups independently. Every individual portfolio is an intersection of a size group and a B/M ratio group. I construct nine size and B/M portfolios within each of the three countries. The portfolios are named as portfolio *ij*, with *i* referring to the size group it belongs to and *j* referring to the B/M ratio group it belongs to. Both size and B/M ratio groups are in ascending order, and the corresponding *i* and *j* range from 1 to 3.[17] For Japan and the UK, the portfolios are rebalanced each July using the previous December's B/M ratio and the previous June's market value. For the US, portfolios are rebalanced each July using last fiscal year-end's B/M ratio and the previous June's market value.

The base returns are the dollar-denominated excess returns on the nine size and B/M portfolios each from Japan, the UK and the US over the Euro–dollar deposit rate. I also include the real gross return of the Euro–dollar deposit to pin down the excess return level.[18]

The summary statistics for the annualized portfolio returns are presented in Fig. 1. In terms of magnitude, all of the UK mean returns and most of the US mean returns are significant, whereas returns from Japan are low and not significantly different from zero, as a result of bearish Japanese market in mid-1990s. If there is a B/M effect, firms with higher B/M ratios should have higher mean returns. If there is a size effect, smaller firms should have higher mean returns. A significant B/M effect exists in Japan and the UK. For the US, the B/M effect is more significant for the smaller firms. However, the size effect is not present in any country, even with more small firms in my sample. Basically, all the models are required to price the international B/M effect.

3.2. International asset pricing models

The first international model is the International single-beta CAPM (ICAPM hereafter), as in Grauer et al. (1976). By assuming the PPP holds, only the exposure to the global market risk is rewarded. The model's unconditional pricing proxy has two factors: a constant, and the excess

[16] DataStream defines book value as net tangible assets, which are equity capital and reserves minus total intangibles. For the US, book value is defined to be the Compustat book value of stockholders' equity, plus balance-sheet deferred taxes and investment tax credit, minus the book value of the preferred stock, as in Fama and French (1993).

[17] For instance, the US nine portfolios are named as US11, US12, US13, US21, US22, US23, US31, US32 and US33.

[18] For the set of 28 base assets, the weighting matrix for the HJ-distance has a condition number smaller than 15,000, which indicates the weighting matrix is well behaved.

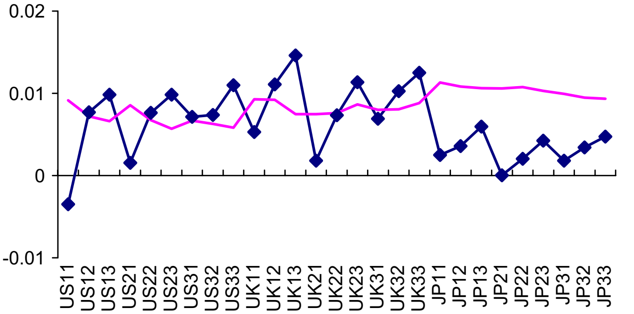


Fig. 1. Summary statistics for monthly returns on country size and B/M portfolios. The sample period is from 1981:7 to 1997:12. Data for Japan and UK firms are obtained from DataStream; data for US firms are obtained from CRSP and Compustat. The numbers on the *x*-axis are the portfolios' names. The first digit in a portfolio name refers to the size group it belongs to, and the second digit refers to the B/M group it belongs to. Both the size groups and the B/M groups are in ascending order. The *y*-axis reports the means and standard errors for the annualized monthly real net returns of each portfolio. The diamonds are the sample average returns, and the line without diamonds is the two-standard-error band for the mean returns.

return on the global market portfolio, WR_{VW}. The WR_{VW} is proxied by the return on the DataStream Global Index[19] over the one-month Euro–dollar deposit rate.

The second model is the International CAPM with exchange risk (hereafter $ICAPM^{EX}$). When there are deviations from PPP, Adler and Dumas (1983) argue that exchange risk is associated with changes in prices and thus constitutes an additional source of risk.[20] I include separate exchange risk factors for the three major foreign currencies: Deutsche mark, Japanese yen and UK pound. They are denoted EXGE, EXJP and EXUK, respectively. The exchange risk factors are calculated as the one-month Euro-deposit rate for each of the foreign currencies compounded by the exchange rate variation relative to the US dollar minus the Euro–dollar deposit rate. Those are essentially excess returns on foreign currency holdings. The exchange rate data are obtained from Data Resources Incorporated (DRI) and reflect the London closing prices on the last day of the month. The unconditional pricing proxy has five factors: the constant, WR_{VW}, EXGE, EXJP and EXUK.

The third model is the Fama and French (1998) empirical international multi-factor model (hereafter IFF3). This model is called "empirical" because its key pricing factors are derived directly from the base portfolio returns without specifying the risk sources. This model assumes that the size effect and B/M effect are common world phenomenon, and they are driven by global risks other than the global market risk. Factors WSMB and WHML are constructed to capture these global risks. Following Fama and French (1998), I first compute SMB's and HML's within individual countries. SMB is the excess return of local small firms over local big firms; HML is the excess return of local high B/M firms over local low B/M firms. WSMB and WHML are the value-weighted sum of the local SMB's and HML's. The IFF3's unconditional pricing proxy has four factors: constant, WR_{VW}, WSMB, and WHML.

[19] The DataStream Global Index is highly (>99.8%) correlated with the MSCI Global Index.

[20] In the original model, exchange risk includes changes in the inflation rates and changes in the exchange rates. But because previous studies find the changes in inflation rates to be non-stochastic and not correlated with asset returns, I identify exchange risk only by exchange rate changes, similar to the simplified model in Dumas and Solnik (1995).

Table 1 presents summary statistics for the risk factors and the business cycle variables. In Panel A, the world market excess return is positive and significant. The exchange risk factors are insignificant because of their big variances. They are highly correlated with each other, because the exchange rate variations are highly correlated, which indicates that the exchange risk factors mainly capture the variations in dollar's value. If the size and B/M effects are present in the local/global market, the Fama–French factors should be positive and significant. Panel B reports mean and standard deviation for the country size factors and the B/M factors. The country size factors have various signs but all are insignificant, while all country value factors are positive and mostly significant. Since the world factors are the value-weighted sum of country factors, WSMB is not significant, while WHML is positive and significant.

3.3. Business cycle variable z_t

As discussed in previous section, all conditional models include one conditioning variable z_t to approximate time-varying risk premiums. For conditioning variables to capture the time-varying risk premiums, they should be able to summarize the current business cycle status. In this article, I consider two business cycle variables.[21] The first one is the cyclical component of the global industrial production index (WIP hereafter), because industrial production is a popular business cycle indicator. Furthermore, Hodrick and Zhang (2001) report that using the cyclical element in the US industrial production index as conditional information helps to explain the size and B/M effects in the United States.

The Euro–dollar deposit rate is the short interest rate in this study. It has been documented in numerous studies that short rates reflect the state of the business cycle because the variations in the short rate correspond to fluctuations in people's expectations of the future discount rate. Therefore, the second conditioning business cycle variable is the cyclical component of the Euro–dollar deposit rate (WIR hereafter).[22]

To obtain the cyclical element of the business cycle variables, I first retrieve from DataStream the time series of the global industrial production index and the Euro–dollar deposit rate starting from January 1970. I use the Hodrick and Prescott (1997) filter on the first 11 years to initialize the cyclical series. The smoothing parameter is set to be 6400. I then recursively use the procedure on available data to find the subsequent elements for the cyclical series. This method guarantees that each element is in the time t information set.

From Table 2, WIP and WIR have relatively low mean, and low correlation with other global pricing factors. These business cycle variables also have high auto-correlation coefficients, and they are highly correlated with each other (correlation = 0.69). Fig. 2 provides the time-series between 1981 and 1997 for both business cycle variables. They roughly display similar ups and downs during this sample period.[23]

[21] No more business cycle variables are considered to save space. My experiment with default premium, another business cycle indicator, gives consistent results.

[22] Because there is no other suitable interest rate for the global market.

[23] From results not shown in the paper, the two measures of global business cycle are highly correlated with their counterparts in individual countries. For instance, correlation(WIP, IPUS) = 82%, correlation(WIP, IPUK) = 41%, and correlation(WIP, IPJP) = 68%. This indicates that individual countries share the global business cycle variations. The data also show that the local business cycle variables, except for US, lag behind the global business cycle variables by 3–6 months.

Table 2
Summary statistics for factors and conditioning variables

Panel A: Summary statistics for conditioning variables

	WR_{VW}	EXGE	EXJP	EXUK	WSMB	WHML	WIP	WIR
Mean (%)	0.65	0.10	0.11	0.19	−0.04	0.38	0.14	−0.77
Std. dev. (%)	0.30	0.20	0.22	0.20	0.15	0.13	0.09	0.92
Correlation								
WR_{VW}		0.17	0.30	0.21	−0.10	−0.29	−0.06	−0.01
EXGE			0.63	0.71	−0.15	−0.14	−0.09	0.04
EXJP				0.45	0.03	−0.07	−0.02	0.09
EXUK					−0.13	−0.10	−0.01	0.03
WSMB						0.10	−0.06	−0.06
WHML							0.04	0.06
WIP								0.69

Panel B: Summary statistics for size premium and value premium

Variable	SMBJP	SMBUK	SMBUS	HMLJP	HMLUK	HMLUS
Mean (%)	0.11	0.08	−0.31	0.29	0.49	0.32
Std. dev. (%)	0.21	0.27	0.22	0.22	0.18	0.18

The sample period is 1981:7–1997:12 (198 observations). WR_{VW} is the excess return over the world market index. EXGE, EXJP and EXUK are exchange factors, constructed as the excess returns of foreign currency holdings. SMB is the excess return of local small firms over local big firms; HML is the excess return of local high B/M ratio firms over local low B/M ratio firms. WSMB is the value-weighted sum of local SMBs, and WHML is the value-weighted sum of local HMLs. Both terms are in US dollars. WIP is the cyclical element in the Hodrick and Prescott (1997) filtered industrial production. WIR is the cyclical element in the Hodrick and Prescott (1997) filtered Euro–dollar deposit rate. Std. dev. is the standard deviation of the mean.

4. Empirical results

4.1. Unconditional models

4.1.1. Summary statistics

The basic diagnostics for unconditional models are presented in Panel A of Table 3. The simplest model incorporates only one constant factor in the stochastic discount factor, and it is called the Null model.[24] Overall, the magnitudes of HJ-distances are mostly between 0.9 and 1. By comparing across models, the ICAPM with exchange risk has the smallest HJ-distance. Thus, it best prices the underlying assets among unconditional models.

The maximal annual pricing errors for any portfolio constructed from base assets, with an annual standard error of 20%, are about 7–9% after adjusting for small sample bias. Consistent with the large errors, none of the unconditional models can pass the HJ-distance equals zero test, including the Fama–French factor model. The *J*-statistics of the optimal GMM provide the same inference. Since the market integration hypothesis requires that there exists at least one international model able to price the international assets, the hypothesis is rejected when we only allow constant betas and risk premiums.

[24] The Null model is used as a benchmark. With only a constant factor present, the distance between y and $\tilde{m}$ is $\delta = \min_{m \in M} std(m)$, which is the standard deviation for the least volatile element in M.

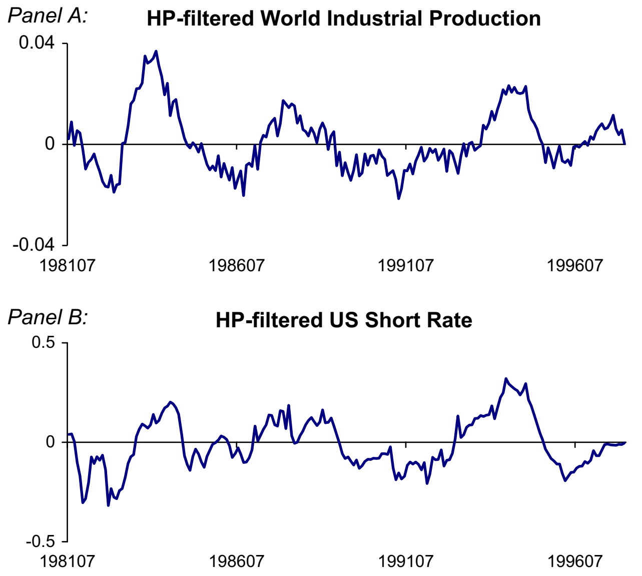


Fig. 2. Business cycle variables. Short rate is the Euro–dollar deposit rate. Both the monthly industrial production index and the one-month Euro–dollar deposit rate are obtained from DataStream. The sample period is from 1981:07 to 1997:12.

I also report the p-values, from the (small sample) empirical and asymptotic distribution, for the HJ-distance test and the optimal GMM test. The p-values from the empirical distribution are always bigger than the asymptotic p-values, which is roughly consistent with the over-rejection claim. However, the inference from empirical p-values does not qualitatively differ from those obtained by using asymptotic p-values. Except for the Null model, all unconditional models can pass the stability test, which is consistent with Ghysels (1998) that unconditional models are stable.

4.1.2. Parameter estimates

Panel B of Table 3 reports the parameter estimates from minimizing the HJ-distance. Factor prices, b, are defined in Eq. (2), and provide information on whether the factor is an important determinant of the pricing kernel. Beta risk premiums, Λ, are defined in Eq. (7), and provide information on whether the risk factors significantly influence the expected returns of the underlying assets. For all unconditional models, the world market risk is always significantly priced. When the exchange risk factors are included, the joint hypothesis of exchange risk factors receiving zero prices is strongly rejected, which demonstrates the importance of exchange risk. Both EXGE and EXUK are important for correct risk specification, and EXGE is significantly priced for the underlying assets, which is consistent with Dumas and Solnik's (1995) finding. For the IFF3, since the B/M effect is significant in my sample, the WHML is significantly priced.

To clarify which of the exchange risk factors and Fama–French factors are more important, I also nest both sets of factors in one model. After being orthogonalized to the Fama–French factors, the exchange risk factors are still jointly significantly priced with a p-value of 0.00. But after being orthogonalized to the exchange risk factors, the Fama–French factor(s) lose significance, and the p-value is 0.38. This indicates that the exchange risk factors may be able to capture the cross-sectional return spreads at least as well as the Fama–French factors.

Table 3
Diagnostics for unconditional models

Panel A: Summary statistics

Model	δ	Max. err. (%)	s.e.(δ)	$p(\delta=0)$	$p^*(\delta=0)$	$p(J)$	$p^*(J)$	supLM	Para. #
Null	1.009	9.19	0.154	0.000	0.000	0.000	0.000	58.784*	1
ICAPM	0.987	8.69	0.150	0.007	0.000	0.000	0.000	3.143	2
ICAPM^{EX}	0.938	7.23	0.156	0.005	0.001	0.001	0.001	11.394	5
IFF3	0.959	8.23	0.147	0.010	0.000	0.000	0.000	6.423	4

Panel B: Parameter estimates: factor prices $\hat{b}$ and beta risk premium $\hat{\Lambda}$

	Constant	WR_{VW}	EXGE	EXJP	EXUK	WSMB	WHML
ICAPM							
$\hat{b}$	1.03	−0.05					
Std. dev.	0.03	0.02					
$\hat{\Lambda}$		0.93					
Std. dev.		0.38					
ICAPM^{EX}							
$\hat{b}$	1.04	−0.05	0.40	−0.10	−0.19		
Std. dev.	0.06	0.03	0.12	0.09	0.10		
$\hat{\Lambda}$		0.99	−1.52	−0.34	−0.24		
Std. dev.		0.48	0.48	0.48	0.39		
IFF3							
$\hat{b}$	1.10	−0.07				0.04	−0.15
Std. dev.	0.05	0.02				0.04	0.05
$\hat{\Lambda}$		0.99				−0.18	0.30
Std. dev.		0.39				0.16	0.14

Monthly data for Japan, the UK and the US are from 1981:07 to 1997:12. Basic assets include the excess returns of the nine size and B/M portfolios from each of the three countries over the one-month Euro–dollar deposit rate, and the gross return on the one-month Euro–dollar deposit. Returns are real returns denominated in dollars. ICAPM is the international single-beta CAPM; ICAPM^{EX} is the international CAPM with separate exchange risk factors for mark, yen and pound; IFF3 is the international Fama–French multi-factor model.
In panel A, δ is Hansen–Jagannathan distance. Max. err. is the maximum annual pricing error for a portfolio ξ when its annual standard error is 20%, as in Eq. (6). The error has been adjusted for small sample bias. s.e.(δ) is standard error for HJ-distance under the hypothesis that $\delta \neq 0$. $p(\delta=0)$ is the asymptotic p-value for the test $\delta=0$ under the null $\delta=0$, $p^*(\delta=0)$ is the corresponding empirical p-value from Monte Carlo experiments. The asymptotic p-value of optimal GMM test is $p(J)$, the empirical p-value of the optimal GMM test is $p^*(J)$. supLM is the value for the supLM test statistics. The asterisk means the model fails the supLM test at the 1% level. Para. # is the number of parameters.
In panel B, the parameters are estimated by minimizing HJ-distance. The factor prices $\hat{b}$ are defined in Eq. (2), the beta risk premiums $\hat{\Lambda}$ are defined in Eq. (7). The standard errors for the parameter estimates are provided in the rows labeled std. dev.

4.1.3. Model performance on cross-sectional returns

To understand how each model prices the underlying assets cross-sectionally, I present the model errors with their standard errors in Fig. 3. The simplest Null model has one constant factor. The constant factor only captures the mean of the correct pricing kernels, which is the inverse of the average riskfree rate. As a result, the models errors are large and the B/M effect stays unexplained in Panel A.

Panel B presents the model errors for ICAPM. Obviously, the B/M return spreads are still large and obvious. This supports Fama and French's claim that world market risk is unable to price the cross-sectional return spreads. However, compared to the model errors of the Null model, ICAPM shifts all errors downward by 0.5%. This indicates that the exposure to

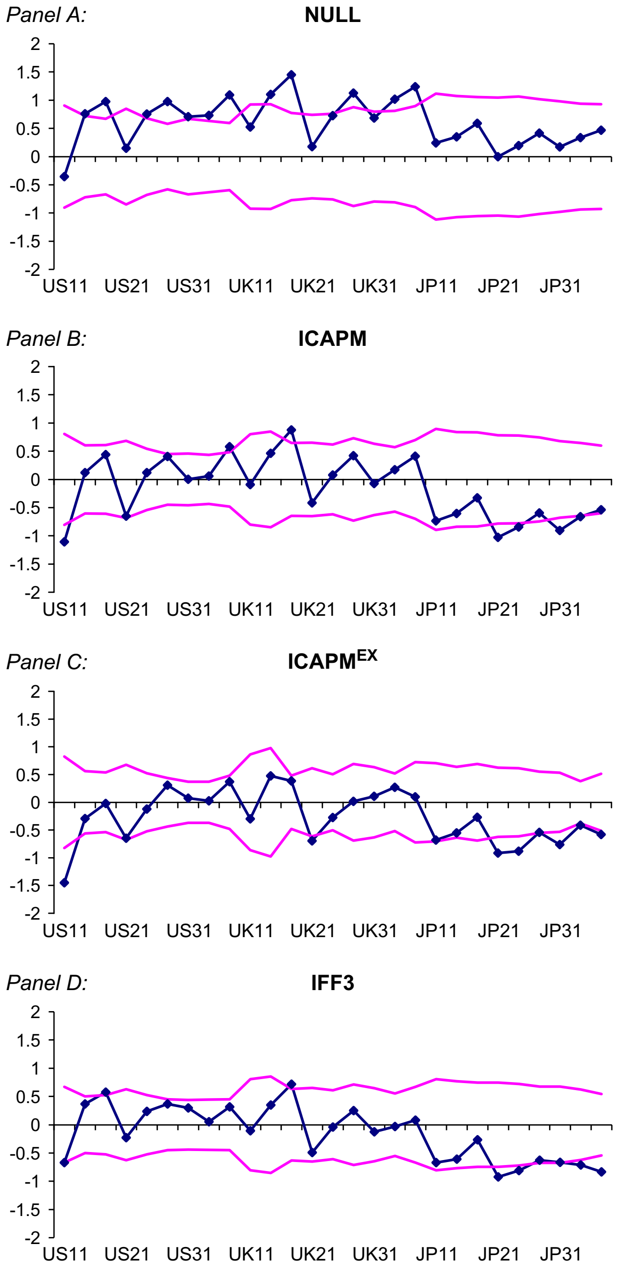


Fig. 3. Model errors for unconditional models. The sample period is from 1981:07 to 1997:12. Basic assets include the excess returns of nine size and B/M portfolios from the US, UK and Japan over the one-month Euro–dollar deposit rate, and the gross return on the one-month Euro–dollar deposit. The returns are real returns denominated in US dollars. The numbers on the x-axis are the portfolios' names. The first digit in the portfolio name refers to the size group it belongs to, and the second digit refers to the B/M group it belongs to. Both the size groups and the B/M groups are in ascending order. The diamonds are the model errors (in % per month) defined in Eq. (B1), the other two lines are two-standard-error bands for the model errors.

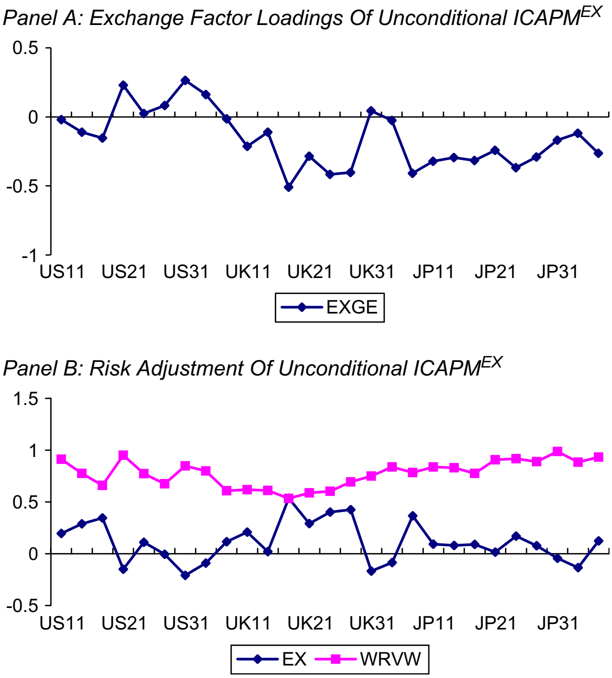


Fig. 4. Unconditional exchange risks. Monthly data are from 1981:07 to 1997:12. Returns are real returns denominated in dollars. The numbers on the x-axis are the portfolios' names. The first digit number in portfolio name is the size group it belongs to, and the second digit is the B/M group it belongs to. Both the size groups and the B/M groups are in ascending order. Factor loadings in Panel A are $\hat{\beta}$, and risk adjustments in Panel B are $\hat{\beta}'\hat{\Lambda}$. Both are defined in Eq. (7).

the world market risk contributes about a 6% annual excess return to every asset. This is why the world market risk is important for international asset pricing.

The model errors for ICAPM^{EX} are presented in Panel C. Adding in the exchange risk factors helps to explain the high returns on value firms in all countries. Consequently, the B/M spreads in model errors are smaller than those for ICAPM, and the model errors are mostly between -0.5% and 0.5% per month. Exchange risk can affect the firm's cash flow through different channels. For instance, it can affect the firm's direct imports and exports, the firm's competition from foreign firms in the same industry, and the firm's global diversification. A firm level investigation is beyond the scope of this article. To get a rough idea about how exchange risk affects individual portfolios, I first examine the pattern of factor loadings β on the exchange risk factors in Fig. 4.

Because of the dominant role of EXGE, Panel A only reports the factor loadings on EXGE. The most obvious pattern is that most of the US firms have positive loadings except small firms, while the UK and Japanese firms have negative loadings. Since I calculate the exchange risk factors as excess returns on foreign currency holdings, when the dollar becomes stronger, the value of EXGE goes down. The positive loadings of most US big firms mean that when the dollar is stronger, they have lower returns. Intuitively, we can interpret big firms as net exporters and small firms as importers. The negative loadings of UK and Japanese firms indicate that when the dollar is stronger, they have higher returns. Both UK and Japanese firms may be net exporters to the US market, or they export more to the US than to Germany.

To measure how important exchange risk is and how it helps to price cross-sectional returns, I examine the total risk adjustment $\beta^{EX}\Lambda^{EX}$ (by summing up $\Lambda_j^{EX}\beta_j^{EX}$, $j = 1, \ldots, 3$) for exchange risk exposures in Panel B. On average, the exposures to the exchange risk are positively rewarded for most firms,[25] and the magnitude is about 3% per year, which is a considerable portion of the average excess returns. Thus, exchange risk is important for international assets. It is interesting to notice that the value firms in the US and UK are compensated more than the growth firms for their exchange risk exposures. There are two possible explanations. One is that value firms are more financially constrained,[26] and are more sensitive to macroeconomic conditions, including exchange rate fluctuations. This higher sensitivity implies a higher return for value firms. On the other hand, previous literature explains the cross-sectional differences in exchange risk exposures by the differences in firms' hedging activities. If the firm hedges more, which reduces its exposure, the reward should be lower. Geczy et al. (1997) argue that because of economies of scale, the larger firms are more likely to hedge against exchange risk than the small firms. So the small firms have higher rewards for exchange risk exposures. Similarly, since growth firms face a more severe under-investment problem given their growth opportunities, they also tend to hedge more against the variation in cash flows induced by exchange risk. Hence, value firms have higher rewards for their exposures. These arguments are consistent with my findings. Overall, exchange risk factors help to price size and B/M portfolios.

The IFF3 is designed to price the international B/M effect. From Panel D of Fig. 3, the model captures the B/M spreads for US and UK big firms. Compared to model errors of ICAPM^{EX}, IFF3 prices the portfolio US11 and Japanese assets better, but it fails to price the B/M spreads for UK small firms. The magnitude of the model errors are around 0.5% per month, and the B/M pattern is still obvious. Hence, the Fama–French factors do not price the B/M effect better than the exchange risk factors.

To summarize, the unconditional models cannot adequately capture the cross-sectional B/M spreads and they fail to pass the specification test.

4.2. Conditional models

Unconditional models may fail because constant betas and constant risk premiums misspecify the behavior of the underlying risks. In this subsection, I examine the implications of the models with time-varying betas and time-varying risk premiums.

4.2.1. Summary statistics

Table 4 reports the summary diagnostics when the business cycle is measured by WIP and WIR. When adding in WIP, the HJ-distances are mostly between 0.7 and 0.8, which are smaller

[25] As pointed out in Glosten et al. (1993), in a conditional setting, it is not certain whether bearing more risks can bring higher returns from time to time. De Santis and Gerard (1998) explicitly calculate the exchange risk premiums over time for national indices returns, to examine whether exchange risk premiums are large and important. They find the exchange risk premiums can have both signs, and they are volatile over time. In this cross-sectional study, parameterization to capture explicit time variation in exchange risk premiums, as in De Santis and Gerard (1998), is not feasible because of large number of parameters. Fortunately, the unconditional return premiums provide enough evidence that exchange risk is important to base assets.

[26] As in Fama and French (1995), high B/M firms usually are under financial distress. These firms have persistently low earnings, higher financial leverage, and more earnings uncertainty.

Table 4
Diagnostics for conditional models

Model	δ	Max. err. (%)	s.e.(δ)	$p(\delta=0)$	$p^*(\delta=0)$	$p(J)$	$p^*(J)$	supLM	Para. #
Panel A: Summary statistics when using WIP to approximate the risk premiums									
Null	0.826	1.73	0.203	0.048	0.212	0.033	0.459	19.831*	2
ICAPM	0.782	0.40	0.195	0.125	0.414	0.447	0.966	19.897*	3
ICAPM^{EX}	0.745	−0.07	0.200	0.187	0.507	0.680	0.978	20.714	6
IFF3	0.764	0.57	0.180	0.098	0.400	0.281	0.908	21.296	5
Panel B: Summary statistics when using WIR to approximate the risk premiums									
Null	0.952	6.76	0.193	0.000	0.000	0.000	0.000	12.929	2
ICAPM	0.928	6.10	0.185	0.000	0.001	0.000	0.000	13.186	3
ICAPM^{EX}	0.820	2.23	0.205	0.072	0.152	0.041	0.208	13.309	6
IFF3	0.916	6.46	0.176	0.000	0.001	0.000	0.000	16.308	5

Monthly data for Japan, the UK and the US are from 1981:07 to 1997:12. Basic assets include the excess returns of the nine size and B/M portfolios from each of the three countries over the one-month Euro–dollar deposit rate, and the gross return on the one-month Euro–dollar deposit. Returns are real returns denominated in dollars. ICAPM is the international single-beta CAPM; ICAPM^{EX} is the international CAPM with separate exchange risk factors for mark, yen and pound; IFF3 is the international Fama–French multi-factor model. WIP is the cyclical element in world industrial production index, WIR is the cyclical element in the Euro–dollar deposit rate. All conditioning variables are lagged one period. δ is Hansen–Jagannathan distance. Max. err is the maximum annual pricing error for a portfolio ξ when its annual standard error is 20%, as in Eq. (6). The error has been adjusted for small sample bias. s.e.(δ) is standard error for HJ-distance under the hypothesis that $\delta \neq 0$. $p(\delta=0)$ is the asymptotic p-value for the test $\delta=0$ under the null $\delta=0$, $p^*(\delta=0)$ is the corresponding empirical p-value from Monte Carlo experiments. The asymptotic p-value of optimal GMM test is $p(J)$, the empirical p-value of the optimal GMM test is $p^*(J)$. supLM is the value for the supLM test statistics. The asterisk means the model fails the supLM test at the 1% level. Para. # is the number of parameters.

than their unconditional counterparts by 15–20%. The smallest HJ-distance is obtained by ICAPM^{EX}(WIP), and it is considered the best model in this paper. The maximum annual pricing errors for any portfolio constructed from base assets, with annual standard error of 20%, are now below 2%. All models pass both the HJ-distance test and the optimal GMM test at the 5% level. However, Null(WIP) and ICAPM(WIP) fail the stability test.

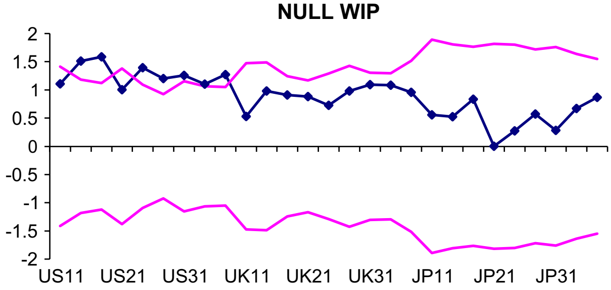
With WIR, the HJ-distances are also smaller than the unconditional counterparts, but the improvements are not as large as in Panel A. After adjusting for small sample over-rejection, only ICAPM^{EX}(WIR) is able to pass both the HJ-distance test and the optimal GMM test. All models conditioning on WIR pass the supLM test.

Since more than one conditional international model passes the specification test, the market integration hypothesis is supported when the betas and beta risk premiums are allowed to vary over time.

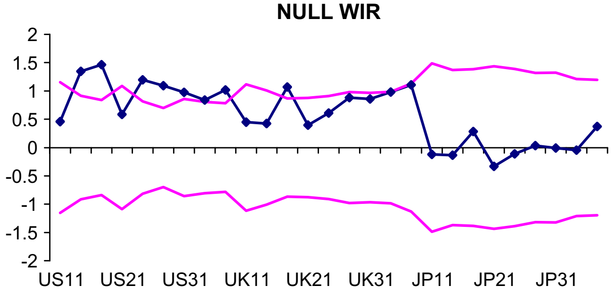
What do business cycle variables capture cross-sectionally? To understand how and why the conditional models with one extra business cycle variable pass the specification test, I conducted several experiments. The results are reported in Fig. 5.

Fig. 5. What can business cycle price? The sample period is from 1981:07 to 1997:12. Basic assets include the excess returns of nine size and B/M portfolios from the US, UK and Japan over the one-month Euro–dollar deposit rate, and the gross return on the one-month Euro–dollar deposit. The returns are real returns denominated in US dollars. The numbers on the x-axis are the portfolios' names. The first digit in the portfolio name refers to the size group it belongs to, and the second digit refers to the B/M group it belongs to. Both the size groups and the B/M groups are in ascending order. In Panels A, and B, the diamonds are the model errors (in % per month) defined in Eq. (B1), the other two lines are two-standard-error bands for the model errors. Factor loadings in Panel C are $\hat{\beta}_z$'s, risk adjustments in Panel D are $\hat{\beta}'\hat{\Lambda}$ and $\hat{\beta}_z'\hat{\Lambda}_z$, as defined in Eq. (7).

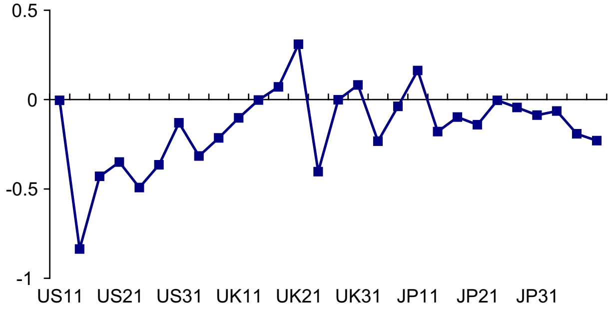
Panel A: Model Errors For Null (WIP)



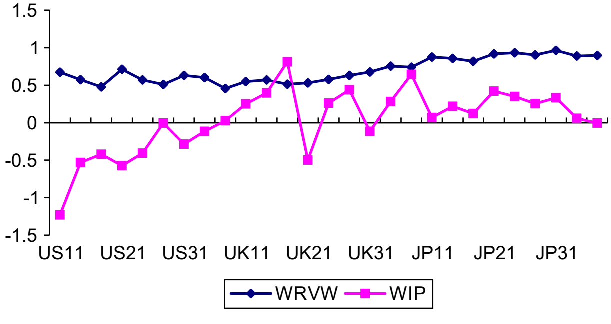
Panel B: Model Errors For Null (WIR)



Panel C: Factor Loadings On WIP In Conditional Null (WIP)



Panel D: Risk Adjustment Of Conditional ICAPM (WIP)



Panels A and B present the model errors of Null(WIP) and Null(WIR). Since the conditional Null models have two factors, the constant and the business cycle variable, this helps to address the explanatory power of the single business cycle variable for the underlying assets. In Panel A, despite the big magnitudes of the model errors, there is no obvious B/M spread in model errors for UK firms and big US firms. But WIP fails to price the B/M spreads for Japanese firms. In Panel B, WIR captures part of the B/M spreads for US and UK firms, and it explains most of the Japanese B/M spreads. In a nutshell, both business cycle variables help to price away most of the cross-sectional B/M spreads.

The explanatory power of business cycle variables for the cross-sectional return spreads implies that B/M spreads may be caused by firms' different sensitivities to time-varying risk premiums, which are directly measured by the premium betas. Panel C reports the factor loadings β_z (the premium beta) on the WIP for Null(WIP).[27] For both US and UK firms, value firms have higher loadings on WIP than the growth firms, which implies that value firms are more sensitive to time-varying risk premiums. This is reasonable because value firms are usually financially stressed, so they are more sensitive to changes in market conditions. Since WIP is positively and significantly priced ($\Lambda_{\mathrm{WIP}} = 6.38$), the higher premium betas of value firms induce higher returns for value firms. This is why the business cycle variables help to price the B/M spread.

But there is one problem with the conditional Null models: they only manage to explain the cross-sectional return differences, not the mean level of excess returns. From the unconditional model errors in previous section, we know that the world market risk helps to pin down the average level of excess returns. Therefore, I expect that ICAPM(WIP), with both $\mathrm{WR}_{\mathrm{VW}}$ and WIP, should be able to capture both the mean level of excess returns and the cross-sectional return spreads. In Panel D, I disaggregate the expected returns into risk adjustments to the market risk premium, $\beta_{\mathrm{WR}_{\mathrm{VW}}}\Lambda_{\mathrm{WR}_{\mathrm{VW}}}$, and the time variation risk premium $\beta_z\Lambda_z$.[28] The world market risk accounts for around 0.6% per month for almost every individual asset, so it does help to match the mean level of excess returns. On the other hand, WIP captures the risk adjustment for the time-varying risk premium, $\beta_z\Lambda_z$, which creates the big B/M spreads (with magnitude between -1% and 1% per month) in returns.

It seems that we can use the conditional ICAPM as a correct model for global risk adjustment because it passes the HJ-distance specification test. However, the model fails the stability test, which indicates that the good performance may be a result of unstable parameters. Next I investigate whether the exchange risk factors and the Fama–French factors have additional explanatory power beyond the business cycle variables, or they only improve parameter stability.

4.2.2. *Exchange risk factors and Fama–French factors versus business cycle variables*

$\mathrm{ICAPM}^{\mathrm{EX}}$(WIP), $\mathrm{ICAPM}^{\mathrm{EX}}$(WIR) and IFF3(WIP) pass the HJ-distance (optimal GMM) specification test at the 5% marginal level of significance, and the stability test at the 1% level.[29] I choose this set of "successful" models to investigate relations between the exchange risk factors, Fama–French factors and the business cycle variables.

The parameter estimates are reported in Table 5. To single out the impact of different risk factors, I orthogonalize the risk factors using the Cholesky factorization. Depending on the order of the factors, I keep the first non-constant risk factor unchanged, then I orthogonalize the

[27] The loadings on WIR in conditional Null models are similar.

[28] To take out possible influence of the world market risk, WIP is orthogonalized to $\mathrm{WR}_{\mathrm{VW}}$.

[29] I choose the 1% level to avoid possible over-rejection in small sample.

Table 5
Parameter estimates for interesting models: factor prices $\hat{b}$ and beta risk premiums $\hat{\Lambda}$

Panel A: Business cycle variables are orthogonalized to other risk factors

	Constant	WR_{VW}	EXGE	EXJP	EXUK	WSMB	WHML	WIP	WIR
ICAPM^{EX}(WIP)									
$\hat{b}$	1.23	−0.05	0.14	−0.01	−0.06			−0.36	
Std. dev.	0.13	0.04	0.07	0.06	0.07			0.09	
$\hat{\Lambda}$		0.94	−2.34	0.16	1.01			6.28	
Std. dev.		0.66	1.25	1.09	1.15			1.60	
ICAPM^{EX}(WIR)									
$\hat{b}$	0.97	−0.06	0.20	−0.05	−0.1				−0.32
Std. dev.	0.12	0.04	0.07	0.07	0.07				0.10
$\hat{\Lambda}$		1.05	−3.53	0.90	1.68				5.44
Std. dev.		0.66	1.20	1.15	1.16				1.70
IFF3(WIP)									
$\hat{b}$	1.27	−0.05				0.01	−0.05	−0.36	
Std. dev.	0.13	0.03				0.03	0.03	0.09	
$\hat{\Lambda}$		0.87				−0.21	0.90	6.26	
Std. dev.		0.58				0.54	0.58	1.50	

Panel B: Other risk factors are orthogonalized to business cycle variables

	Constant	WR_{VW}	WIP	WIR	EXGE	EXJP	EXUK	WSMB	WHML
ICAPM^{EX}(WIP)									
$\hat{b}$	1.23	−0.05	−0.38		0.11	0.01	−0.03		
Std. dev.	0.13	0.04	0.09		0.07	0.06	0.07		
$\hat{\Lambda}$		0.94	6.51		−1.82	−0.24	0.44		
Std. dev.		0.66	1.58		1.25	1.1	1.17		
ICAPM^{EX}(WIR)									
$\hat{b}$	0.97	−0.06		−0.31	0.22	−0.03	−0.1		
Std. dev.	0.12	0.04		0.1	0.07	0.07	0.07		
$\hat{\Lambda}$		1.05		5.33	−3.77	0.44	1.68		
Std. dev.		0.66		1.69	1.23	1.14	1.16		
IFF3(WIP)									
$\hat{b}$	1.27	−0.05	−0.36					−0.01	−0.04
Std. dev.	0.13	0.03	0.09					0.03	0.03
$\hat{\Lambda}$		0.87	6.28					0.22	0.71
Std. dev.		0.58	1.5					0.53	0.59

Monthly data for Japan, the UK and the US are from 1981:07 to 1997:12. Basic assets include the excess returns of the nine size and B/M portfolios from each of the three countries over the one-month Euro–dollar deposit rate, and the gross return on the one-month Euro–dollar deposit. Returns are real returns denominated in dollars. The parameters are estimated by minimizing HJ-distance. The factors are orthogonalized using Cholesky factorization in the order listed. The factor prices $\hat{b}$ are defined in Eq. (2), the beta risk premiums $\hat{\Lambda}$ are defined in Eq. (7). The standard errors for the parameter estimates are provided in the rows labeled std. dev.

second factor with respect to the first, then the third with respect to the first two factors, and so on. The last factor in the model is orthogonal to all other factors.

In Panel A, I examine the significance of the business cycle variables by putting them at the end of the list. From the last two columns, both orthogonalized business cycle variables are significant with p-values smaller than 1%, implying that time-varying risk premiums are important to price the international B/M effect. The world market risk is marginally priced for all three models. For the conditional ICAPM with exchange risk, EXGE stays important for the pricing kernel and for the underlying assets. For the conditional IFF3, the WHML is also marginally priced. Note that in conditional IFF3, WIP is orthogonalized to market risk, WSMB and the WHML, but it is still significantly priced. This implies that the Fama–French factors leave out something, which may be important to price the international B/M effect.[30]

In Panel B, I exchange the orthogonalization order by orthogonalizing all other factors to the market risk and the business cycle variable. If the exchange risk factors and Fama–French factors capture different components of the excess returns than those captured by the business cycle variables, they should stay significant. For ICAPM^{EX}(WIP), the EXGE is marginally significant; for ICAPM^{EX}(WIR), the EXGE is significant. This indicates that exchange risk factors have additional explanatory power to the business cycle variables, especially when using WIR. But for the conditional IFF3, neither of the Fama–French factors is significant. This indicates that the relevant information the Fama–French factors contain is a subset of what the business cycle variables contain.

Fig. 6 presents model errors for conditional models, and we can examine whether the additional factors improve the model errors. The first model is the ICAPM^{EX}(WIP). In Panel A, there are no obvious B/M spreads in the model errors, and all model errors are around zero except for the median-sized Japanese firms. Panel B presents the risk adjustments for exchange risk exposures. To capture the pure effect of exchange risk, the exchange risk factors are orthogonalized to the WIP. The magnitudes of risk adjustments to exchange risk factors are still comparable to those of business cycle variables. In particular, the rewards for the orthogonalized exchange risk exposures are still around 3% per year for both US and UK firms. For Japanese firms, the risk adjustments are big and negative, which help to price the low returns. From results not shown, the factor loadings on the exchange risk factors are very similar to the unconditional case.

The second model is ICAPM^{EX}(WIR). From Panel C, ICAPM^{EX}(WIR) has bigger model errors on the US small growth firms, and UK big firms than the ICAPM^{EX}(WIP). The model errors on median-sized Japanese assets are significant. Since the difference between the two models is the business cycle variable, it indicates that WIR is less capable than WIP in pricing the cross-sectional spreads. I also examine the pure exchange risk effect for ICAPM^{EX}(WIR), and the results are presented in Panel D. Since WIR has weaker explanatory power than WIP in capturing the B/M spreads, the exchange risk is more important in capturing international B/M effect than in the above case, especially for the UK assets. To summarize, the exchange risk factors are important even in the presence of the business cycle variables.

The last model is the IFF3 conditioning on WIP. In panel E, the model errors of conditional IFF3 are not very different from those of the conditional ICAPM. So in the existence of WIP, adding in Fama–French factors do not improve model errors. Furthermore, after being orthogonalized to WIP, the WHML factor fails to generate B/M spreads for the UK firms and most Japanese firms. Even though WHML can still generate B/M spreads for US firms, the magnitudes are trivial, comparing to the risk adjustments for WIP.

Overall, all evidence points to the conclusion that the B/M effect is at least partially generated by differences in firms' sensitivities to macroeconomic conditions, which are captured by

[30] Within the context of US domestic asset pricing, Ferson and Harvey (1999) argue that the Fama-French factors fail to capture conditional information.

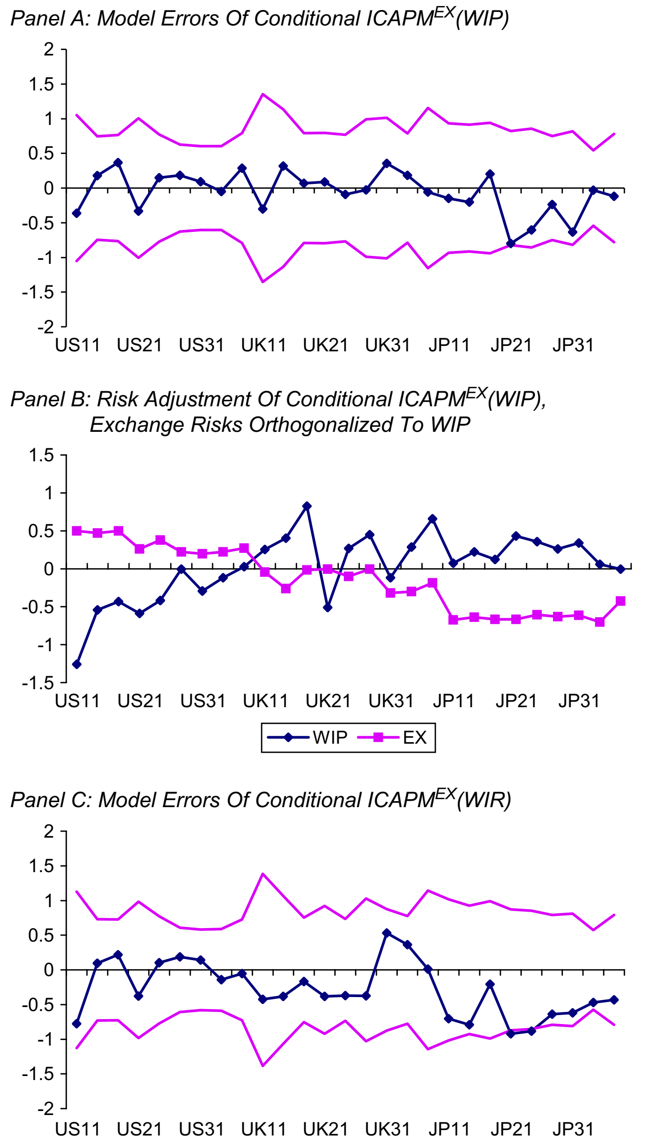


Fig. 6. Business cycle versus exchange risk factors and WHML. Monthly data are from 1981:07 to 1997:12. Returns are real returns denominated in dollars. The numbers on the *x*-axis are the portfolios' names. The first digit in portfolio name refers to the size group it belongs to, and the second digit refers to the B/M group it belongs to. Both the size groups and the B/M groups are in ascending order. In Panels A, C and E, the diamonds are the model errors (in % per month) defined in Eq. (B1), the other two lines are two-standard-error bands for the model errors. Panels B, D and F report risk adjustments $\hat{\beta}'\hat{\Lambda}$ and $\hat{\beta}_z'\hat{\Lambda}_z$, as defined in Eq. (7).

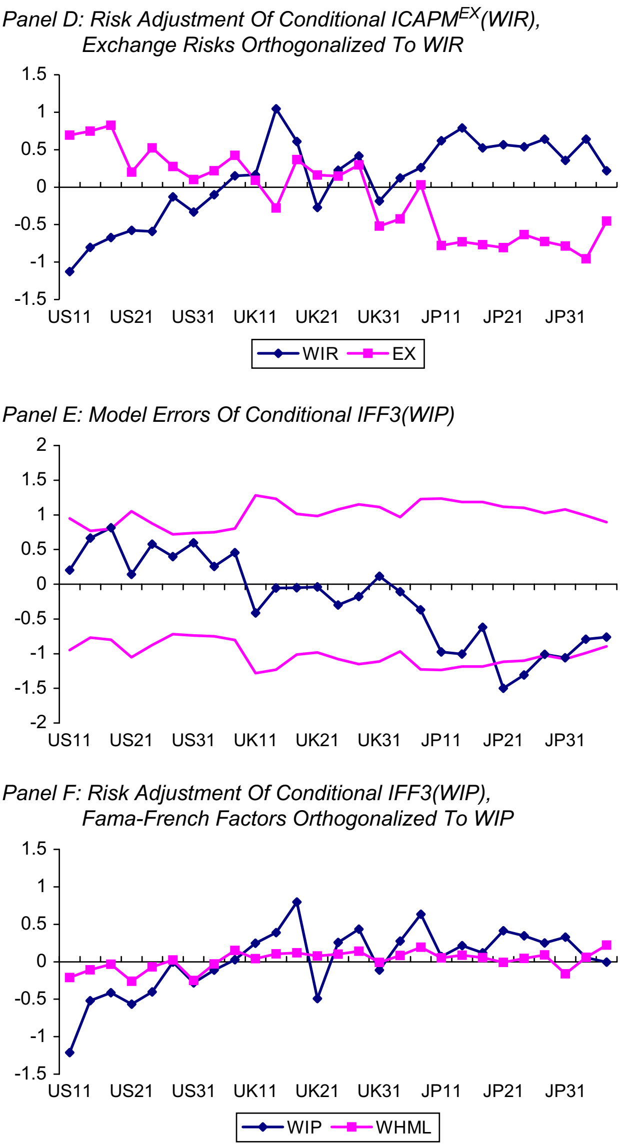


Fig. 6. (*continued*).

time-varying betas and risk premiums. The Fama–French factors capture part of this relevant information. But once orthogonalized to this relevant information, the Fama–French factors are no longer priced. Vassalou (2003) also argues that Fama–French factors are priced just because they contain information that predicts future GDP growth.[31]

[31] Because of space limit and data availability, I do not explore more business cycle variables in this paper. But my simple experiment with the US default premium reveals that it also helps to price the B/M effect.

4.2.3. Beat the best model

Since the ICAPM^{EX}(WIP) has the smallest HJ-distance (0.07% annual maximal error), it is the best model for pricing the international size and B/M portfolios. Note that the HJ-distance is the maximum pricing error for the normalized portfolio γ. As long as the model has a non-zero HJ-distance, we should invest in the portfolio γ to take the biggest advantage of the model's mispricing. As demonstrated in previous sections, this portfolio γ's weights are linear functions of the multipliers λ, defined in Eq. (4).

Table 6 reports the λ's with their standard errors. An asterisk implies that the corresponding weight is significant at 5% level. To beat the benchmark in ICAPM^{EX}(WIP), the investors should have big offsetting positions on US small and big firms and Japanese median size firms, to arbitrage against the B/M spreads. Those weights are consistent with the largest model errors of the model. We can normalize the vector of λ to make the weights sum up to one. After this standardization, the weights range from −200% to 200%. Since this portfolio may be hard to implement in reality, the benchmark in ICAPM^{EX}(WIP) is hard to beat.

5. Country-specific factors

Before the 1980s, most investors were restricted to their home country assets, and they used the domestic benchmark to price domestic assets. From the discussion above, we know that, for my sample period 1981–1997, several conditional models pass the HJ-distance specification test, and the market integration hypothesis cannot be rejected. One important question arises: does market integration mean that the domestic models are all incorrectly specified and the country factors are not relevant? My answer to this question is that if the world market is integrated, country factors might be priced due to their non-zero correlations with global risk factors, while country-specific factors should not be priced.

5.1. Country factors versus country-specific factors

Country factors refer to risk factors calculated within the local market. For instance, the US country market factor is the excess return of the US market index. Obviously, the country

Table 6
Multipliers λ for conditional ICAPM^{EX} with WIP

Portfolio	λ	s.e.(λ)	Portfolio	λ	s.e.(λ)	Portfolio	λ	s.e.(λ)
US11	−25.3*	8.6	UK11	−0.7	3.3	JP11	8.5	8.7
US12	22.8*	13.1	UK12	3.9	3.1	JP12	−6.1	9.9
US13	16.4	10.2	UK13	−0.9	5.8	JP13	22.9*	8.4
US21	−1.7	6.9	UK21	−1.8	5.7	JP21	−23.9*	8.9
US22	−5.2	9.2	UK22	−1.2	9.2	JP22	−10.6	11.2
US23	−0.2	8.1	UK23	−3.4	4.6	JP23	−4.7	12.5
US31	12.2	7.8	UK31	3.9	7.0	JP31	−1.2	6.1
US32	−11.3	7.9	UK32	0.0	7.7	JP32	15.4*	8.2
US33	2.0	6.4	UK33	0.0	5.0	JP33	0.9	5.8
RFUS	−0.6	0.1						

Monthly data for Japan, the UK and the US are from 1981:07 to 1997:12. Basic assets include the excess returns of the nine size and B/M portfolios from each of the three countries over the one-month Euro–dollar deposit rate, and the gross return on the one-month Euro–dollar deposit. Portfolios are numbered *ij* with *i* indexing size increasing from 1 to 3 and *j* indexing book-to-market ratio increasing from 1 to 3. The Lagrangian Multipliers, λ's, are defined in Eq. (4). s.e.(λ) are their standard errors, an asterisk indicates the parameter is significant at the 5% level.

factors can be correlated with the global risk factors. On the other hand, country-specific factors are calculated within the local market, *but* they are orthogonal to the global risk factors. As noted in Stulz (1995), suppose the world market is actually integrated, and one global pricing proxy y is correctly specified, then

$$E\left(yR_{ij}\right) = E\left[(b'F)R_{ij}\right] = p, \quad i = 1,\ldots,L,\ j = 1,\ldots,N_i.$$

Define the domestic pricing proxy for country i as $y_i^L = \left(b_i^L\right)' F_i^L$, where F_i^L refers to domestic factors. We can always write down the following regression: $F_i^L = a'F + \varepsilon_i$, then $y_i^L = \left(b_i^L\right)'(a'F + \varepsilon_i)$. For assets in country i,

$$E\left(y_i^L R_{ij}\right) = E\left[\left(b_i^L\right)'(a'F + \varepsilon_i)R_{ij}\right] = E\left[\left(b_i^L\right)' a'FR_{ij} + \left(b_i^L\right)' \varepsilon_i R_{ij}\right], \quad j = 1,\ldots,N_i.$$

If $ab_i^L = b$ (the domestic factors have non-zero correlations with the relevant global factors), and $E(\varepsilon_i R_{ij}) = 0$ (the domestic factors do not contain more relevant/priced information than the global risk factors do), this domestic pricing proxy can give the domestic assets correct prices as the correct global pricing proxy does. Note as long as $a \neq 0$, the country factors, F_i^L, will be priced due to their correlations with the relevant global factors. As a result, priced country factors are consistent with market integration hypothesis.

But the country-specific factors, which are orthogonal to the global factors ($a = 0$), will not be priced under the market integration hypothesis. Priced country-specific factors support market segmentation hypothesis. One way to examine the robustness of the market integration hypothesis and the international models is to see whether the country-specific factors are priced.

5.2. Are country-specific factors priced?

Denote y^* as a correct international pricing kernel. By minimizing the HJ-distance, we obtain estimate $\hat{y}^*$ for y^*, and the sample model errors are not significantly different from zero (under the null). I construct an auxiliary pricing kernel y^{A} as

$$y_t^{\mathrm{A}} = c_1 \hat{y}_t^* + c_2' \varepsilon_t^L, \tag{12}$$

where ε_t^L represents a $k \times 1$ vector of country-specific risk factors (orthogonal to y^*), and c_2 is a $k \times 1$ vector of factor risk prices. Given that $\hat{y}^*$ captures all relevant risks, we should have $c_1 = 1$ and $c_2 = 0$. To construct ε_t^L, I need to first find F_t^L, then orthogonalize it with respect to global factors in y^*.

For one country factor to be included, it should have the potential to price the size and B/M effect. Since the US has the largest market capitalization and it usually leads the global business cycle, it is more likely that US factors matter for international assets. Consequently, I report results with the country-specific factors from the US. Fama and French (1996) argue that the Fama–French three-factor model is able to price the US size and B/M portfolios. Griffin (2002) also argues that the US domestic SMB and HML are more relevant than the WSMB and WHML for international asset pricing. Meanwhile, Hodrick and Zhang (2001) report that the cyclical element of US industrial production helps to price the US assets. Hence, I use the three factors from the domestic Fama–French factor model and the US IP as the country factors. The US market return, R_{VW} is proxied by the CRSP value-weighted index return over the one-month Euro–dollar deposit rate. The data for the other factors are obtained from the authors.

Table 7
Robustness check for the international models

Panel A: Unconditional models						
	ICAPM	Constant	R_{VW}	IP	SMB	HML
$\hat{c}$	0.70	0.49	−0.02	−0.32	0.00	−0.01
s.e.	0.61	0.61	0.03	0.07	0.03	0.03
	ICAPM^{EX}	Constant	R_{VW}	IP	SMB	HML
$\hat{c}$	0.73	0.44	−0.02	−0.28	0.02	0.00
s.e.	0.33	0.35	0.03	0.07	0.03	0.03
	IFF3	Constant	R_{VW}	IP	SMB	HML
$\hat{c}$	0.69	0.50	−0.02	−0.32	0.01	0.03
s.e.	0.39	0.40	0.03	0.07	0.03	0.03
Panel B: Conditional models with WIP						
	ICAPM	Constant	R_{VW}	IP	SMB	HML
$\hat{c}$	1.03	0.01	−0.04	0.02	−0.01	−0.02
s.e.	0.26	0.30	0.04	0.12	0.03	0.04
	ICAPM^{EX}	Constant	R_{VW}	IP	SMB	HML
$\hat{c}$	1.04	−0.02	−0.01	0.06	0.01	−0.02
s.e.	0.27	0.31	0.04	0.13	0.04	0.04
	IFF3	Constant	R_{VW}	IP	SMB	HML
$\hat{c}$	1.05	−0.02	−0.05	0.02	−0.01	0.02
s.e.	0.25	0.29	0.04	0.13	0.03	0.04
Panel C: Conditional models with WIR						
	ICAPM	Constant	R_{VW}	IP	SMB	HML
$\hat{c}$	1.51	−0.22	−0.03	0.00	−0.01	−0.02
s.e.	0.35	0.31	0.03	0.11	0.03	0.04
	ICAPM^{EX}	Constant	R_{VW}	IP	SMB	HML
$\hat{c}$	0.98	0.27	−0.01	0.06	0.03	−0.01
s.e.	0.26	0.23	0.04	0.12	0.03	0.04
	IFF3	Constant	R_{VW}	IP	SMB	HML
$\hat{c}$	1.45	−0.19	−0.04	−0.02	0.00	0.02
s.e.	0.29	0.26	0.03	0.10	0.03	0.03

Monthly data for Japan, the UK and the US are from 1981:07 to 1997:12. Basic assets include the excess returns of the nine size and B/M portfolios from each of the three countries over the one-month Euro–dollar deposit rate, and the gross return on the one-month Euro–dollar deposit. Returns are real returns denominated in dollars. The parameter estimates are for the auxiliary pricing kernel defined in Eq. (12). The third column of each panel contains the parameter for the pricing kernel estimated in the first stage. All other columns contain US country-specific risk factors. R_{VW} is the US excess market return, IP is the HP-filtered US industrial production, SMB and HML are Fama–French factors from the US market. The parameters are estimated by minimizing HJ-distance. The factors are orthogonalized using Cholesky factorization in the order listed. The factor prices $\hat{c}$ are defined in Eq. (12). The standard errors for the parameter estimates are provided in the rows labeled s.e.

The results for the robustness check are reported in Table 7. For all conditional models in Panels B and C, none of the country risk factors, including local Fama–French factors and local business cycle variable, are priced. Thus, country-specific factors do not improve the explanatory power for the conditional international models, and we cannot reject $c_2 = 0$. For the pricing proxies to be correct and robust, we also need $c_1 = 1$. This restriction is not rejected for all conditional models that pass HJ-distance test. But for the remaining models, ICAPM(WIR) and

IFF3(WIR), c_1 is marginally different from one. In a nutshell, all conditional models that pass the HJ-distance test are robust to inclusion of country-specific factors, and none of country-specific factors are priced.

I also present the results for unconditional models in Panel A. Although we know that they are misspecified and they are not able to satisfy the two restrictions, this provides a chance to examine whether country factors complement the risks missed in the unconditional models. Indeed, both restrictions are rejected for the unconditional models. Among the four country factors, only the US IP is significantly priced. This probably is due to the high correlation (over 80%) between USIP and WIP. This indicates that to capture the international B/M effect, we need to add time variation in betas and risk premiums to the unconditional models, instead of country-specific factors. Interestingly, neither of the Fama–French country factors, orthogonalized to US IP, is significantly priced. So even for the country factors, Fama–French factors only capture part of the information related to the firms' sensitivity to macroeconomic conditions.[32]

6. Conclusion

This paper evaluates alternative international asset pricing models by the Hansen and Jagannathan (1997) distance metric. The HJ-distance methodology provides both a mispricing measure and a model specification test. The base assets are the size and B/M portfolios from Japan, the UK and the US. Since the size effect is not evident in most of the countries, the asset pricing models are mainly required to price the strong international B/M effect.

All international models are specified under the market integration hypothesis, which implies that only the global risks are priced, and the prices are uniform across countries. None of the unconditional models, which impose constant betas and constant risk premiums, can pass the HJ-distance test. Then I allow time-varying betas and time-varying risk premiums by assuming that the models hold conditionally. Adding in time variation greatly improves the performance of each model, so most of the conditional models can pass the HJ-distance test and the market integration hypothesis is supported. Specifically, the conditional ICAPM with exchange risk obtains the smallest HJ-distance.

I approximate the time-varying risk premiums by either one of two business cycle variables: the HP-filtered global industrial production and the HP-filtered short interest rate. Factor loadings indicate that value firms are more sensitive to the time-varying risk premiums than growth firms. Since the business cycle is always positively and significantly priced, value firms enjoy higher returns than growth firms because of their higher loadings. In fact, the business cycle variables capture most of the cross-sectional B/M spreads, especially when the HP-filtered industrial production is used. The IP variable can completely explain UK B/M effect, but it cannot explain the B/M effect for Japanese portfolios.

Exchange risk factors are significantly priced in both unconditional models and conditional models. Individual assets are rewarded by around 3% per year for their exposures to exchange risk. The exchange risk with respect to the mark is the most significantly priced. Since the individual size and B/M portfolios load differently on the exchange risk factors,

[32] Another interesting test is to examine whether the country-specific factors are priced for local assets. From results not reported, when the country-specific factors are orthogonalized w.r.t. global factors, they are mostly not significantly priced for the local assets. This also supports market integration hypothesis.

exchange risk helps to price the B/M spread, even after being orthogonalized to the business cycle.

Fama and French (1998) construct a value premium factor in their multi-factor model to price the international B/M effect. However, the value premium loses its significance after being orthogonalized to the business cycle variables. This implies that the Fama–French factors only contain partial information related to time-varying betas and time-varying risk premiums. When this information is taken out, the Fama–French factors become redundant.

Finally, I include country-specific factors in the international models to see whether they are relevant for international asset pricing. If the international models are correctly specified, none of the country-specific factors should be priced. The conditional models that pass HJ-distance test are found to be robust to the inclusion of country factors, and none of the country-specific factors are priced.

There are several directions in which this study can be extended. First, I do not impose the non-negativity restriction when estimating the correct pricing kernel. Since I include volatile business cycle variables as risk factors, this assumption may be violated. Second, for Japan, since economic development does not follow a smooth path, there could be several structural breaks in the return series. However, in the HJ-distance methodology, the market structure is assumed to be fixed during the sample period, and the return series are assumed to be stationary. A model with structural breaks may be able to better characterize the Japanese asset returns. Finally, I conduct the asset pricing tests assuming the world capital market is perfect with no transaction costs. This assumption may not be realistic.

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Appendix A. Denomination of returns and factors

In this article, I assume that people from different countries have access to a common set of assets, and I denominate the asset returns and the risk factors in dollars. But there may be a demand for using different currencies as the denomination reference currency. This appendix illustrates the impact on the results if I choose another currency to be the denomination currency.

If the world market is integrated, there should exist a set of correct pricing kernels which are able to price international assets for any investor, regardless of the denomination currency. Suppose one correct pricing kernel, $m^{\$}$, is denominated in dollars. It should be able to price all asset returns denominated in dollars, that is, $E_t(m^{\$}_{t+1}R^{\$}_{j,t+1}) = p, \ \ \forall j = 1, \ldots, N$. Define a yen-denominated pricing kernel as

$$m_{t+1}^{¥} = \frac{s_t^{¥/\$}}{s_{t+1}^{¥/\$}} m_{t+1}^{\$},$$

then

$$E_t\left(m_{t+1}^{¥} R_{ij,t+1}^{¥}\right) = E_t\left[m_{t+1}^{¥}\left(R_{ij,t+1}^{\$}\frac{s_{t+1}^{¥/\$}}{s_t^{¥/\$}}\right)\right] = p, \quad \forall i = 1,\ldots,L, \quad \forall j = 1,\ldots,N_i. \tag{A1}$$

So $m_{t+1}^{¥}$ is able to price all yen-denominated returns. Thus, the existence of a correct pricing kernel in US dollars, $m^{\$}$, guarantees the existence of a corresponding correct pricing kernel in ¥, $m^{¥}$. In this sense, the market integration hypothesis is not currency sensitive.

Since all the pricing proxies are linear factor models in this paper, I assume $m^{\$} = b^{\$\prime}F^{\$}$, and $m^{¥} = b^{¥\prime}F^{¥}$. The priced world risks factors, $F^{\$}$ and $F^{¥}$, stand for the same global risks in respective pricing kernels. However, risk prices, $b^{\$}$ and $b^{¥}$, may be very different when using different denomination currencies. We can rewrite Eq. (A1) as

$$\begin{aligned} E_t\left(b^{¥\prime}F_{t+1}^{¥}R_{ij,t+1}^{¥}\right) &= E_t\left[b^{¥\prime}\left(F_{t+1}^{\$}\frac{s_{t+1}^{¥/\$}}{s_t^{¥/\$}}\right)\left(R_{ij,t+1}^{\$}\frac{s_{t+1}^{¥/\$}}{s_t^{¥/\$}}\right)\right] = E_t\left[b^{¥\prime}\left(\frac{s_{t+1}^{¥/\$}}{s_t^{¥/\$}}\right)^2\left(F_{t+1}^{\$}R_{ij,t+1}^{\$}\right)\right] \\ &= E_t\left(b^{\$\prime}F_{t+1}^{\$}R_{ij,t+1}^{\$}\right) \end{aligned}$$

No simple relation between $b^{\$}$ and $b^{¥}$ can be derived if the exchange rate is correlated with the risk factors $F^{\$}$ or the asset returns $R_{ij}^{\$}$. If the exchange rate follows a white noise process and is not correlated with $F^{\$}$ and $R_{ij}^{\$}$, then

$$b^{¥}E\left[\left(\frac{s_{t+1}^{¥/\$}}{s_t^{¥/\$}}\right)^2\right] = b^{\$}.$$

Appendix B. Parameter estimation using HJ-distance and comparison between HJ-distance and other measures

Hansen and Jagannathan note that the parameters in y can be estimated by minimizing δ. First, define the model error vector $g = E(yR - p)$, with its sample counterpart

$$g_T = \frac{1}{T}\sum_{t=1}^{T} R_t y_t - p, \tag{B1}$$

and define the weighting matrix $W = E(RR')^{-1}$ with sample counterpart

$$W_T = \left(\frac{1}{T}\sum_{t=1}^{T} R_t R_t'\right)^{-1}.$$

Then, by squaring Eq. (5),

$$b = \arg\min\ g_T' W_T g_T.$$

Define the sample gradient as

$$D_T = \frac{\partial g_T}{\partial b} = \frac{1}{T}\sum_{t=1}^{T} R_t F_t'.$$

Then the analytical solution for b is given by

$$\hat{b} = \left(D_T' W_T D_T\right)^{-1}\left(D_T' W_T p\right).$$

While the HJ-distance estimation is a standard GMM problem with the moment condition $g_T = 0$, it is not the optimal GMM of Hansen (1982), which uses as the weighting matrix a consistent estimator of $W^* \equiv [T\,\mathrm{var}(g_T)]^{-1} = (S_T)^{-1}$. The specification test statistic of the optimal GMM is $J = Tg_T'(\hat{b})W^* g_T(\hat{b}) \xrightarrow{d} \chi^2(n-k)$. It is obvious that since g_T changes with different models, $W^*$is also model-dependent and that it rewards models with noisy model errors. This makes the J-statistic less suitable for comparing competing models. But the weighting matrix for HJ-distance, $W = E(RR')^{-1}$, is invariant across competing models. This allows us to have a uniform measure of performance across models for a common set of assets. The only assumption needed is that W is non-singular, which is always true in this study. Below I report statistics from both HJ-distance and optimal GMM, but few differences exist in test statistics between the two.

To avoid singularity, Cochrane (1996) uses the identity matrix as the weighting matrix for the GMM minimization. By assigning equal weights to all base assets and ignoring cross-products of model errors, the approach minimizes the sum of squared model errors. This approach is equivalent to a traditional ordinary least square approach, as in Gibbons et al. (1989). However, the statistics are relatively uninformative for this study: most of the models are not rejected just due to large standard errors. The two-pass regression method developed by Fama and Macbeth (1973) is another popular approach for cross-sectional asset pricing. The measure of model performance is the R^2 of the cross-sectional regression of average returns on the betas, which tells us by how much the beta risks can explain the returns. However, since R^2 does not have a well-defined distribution, this approach does not provide a model specification test as GMM-based approaches do. Another competing approach is maximum likelihood, which is the most efficient asymptotically. But since we need to specify the distribution of the error terms, it is not as flexible as the GMM approach in terms of handling conditional heteroskedasticity. Moreover, since this study only examines linear factor models, the test statistics obtained from maximum likelihood are equivalent to those obtained from the optimal GMM, according to Newey and West (1987).

Appendix C. Monte Carlo simulation for HJ-distance and optimal GMM

If an asset pricing model is correct, it determines the expected returns of individual assets by the covariances between the risk factors and the returns. From Eq. (1), this is

$$E(R) = \frac{p - \mathrm{cov}(m, R)}{E(m)}.$$

The Monte Carlo simulation starts from generating return time-series under the null hypothesis of correct asset pricing, and then calculates the empirical distribution of the test statistics. The simulated time-series observations should replicate all relevant time-series characteristics of the original sample observations, for instance, the conditional heteroskedasticity. But the linear asset pricing models only need a simpler procedure. Since the HJ-distance is an analytical function of the unconditional first and second sample moments, we only need to generate time-series observations that match the first and second unconditional moments to calculate the empirical distribution of the test statistics.

The procedure is as follows. First, I take the sample means for the risk factors, expected asset returns under the null hypothesis, and the sample covariances for factors and returns. Second, since the sample means and covariances have posterior distributions of normal distribution and Inverted Wishart distribution, respectively, I draw posterior means and covariances from the respective posterior distributions. Third, I generate t (=197) IID observations from the posterior means and variances. Fourth, I calculate the HJ-distance using the sample means and covariances from the generated IID sample. Finally, the procedure is repeated 10,000 times to find the empirical distribution of HJ-distance under correct asset pricing.

However, this approach is not sound for the optimal GMM. Different from HJ-distance methodology, the optimal GMM test statistic is not an analytical function of the unconditional moments and has to be estimated over the time-series observations. Thus, the optimal GMM statistic is also determined by the time-series properties of the observations. Since the focus of this paper is HJ-distance, I only calculate the empirical distribution of optimal GMM for the simplest case, where I overlook the time-series properties. So I estimate the J-statistic using the IID observations generated from the third step above, and then calculate the empirical distribution. Since this empirical distribution may not be the optimal, I always present the asymptotic p-values for comparison. But as found in the results, the empirical p-values of optimal GMM are always similar to the empirical p-values of the HJ-distance.

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