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Digesting anomalies: A q-factor approach for the Thai market[☆]

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ABSTRACT

We study the extent to which a q-factor approach explains other cross-sectional factor returns in the Thai market from 2000 to 2019. Univariate statistics of the q-factor premia show that the Thai factors have almost double the statistical and economic significance compared to US factors. While the q-factor model and the Fama-French six-factor model have similar performances in the US, they do not in Thailand. We find that the q-factor model reduces the t-statistics of the alphas for 13 out of 15 anomalies when compared to the six-factor model. Our findings suggest that the q-factor model is a better empirical asset pricing model in Thailand, showing external validity of the model even in an emerging market.

1. Introduction

The innovation of Hou et al. (2015) was the introduction of a theoretically driven factor model which at least matched or outperformed the Fama-French three-factor or four-factor model. But while the Fama-French three- to five-factor framework has been tested in emerging markets (e.g., Foye, 2018), the investment capital asset pricing model-based alternatives per Hou et al. (2015) have not been tested. Comparing the Fama-French model's performance to the q-factor model's performance is important as the latter is theoretically motivated with a neoclassical model. In addition, Hou et al. (2019) show that the Hou et al. (2015) q-factor model in the US subsumes both the Fama-French five-factor and six-factor models.[1]

This paper tests whether the q-factor asset pricing model that includes profitability and investment factors can better explain equity returns than the Fama-French six-factor model in Thailand. While our US findings are consistent with Hou et al. (2019) that the two models have similar performance, the q-factor model performs better in Thailand, reducing the t-statistics of the alphas for 13 of the 15 sets of test portfolios compared to the Fama-French model. Most notably, the book-to-market anomaly – which is part of the Fama-French model but not the q-factor model – is not priced.

There are three reasons why studying the Thai market is informative for both practitioners and academics. First, although the Thai

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[1] In Hou et al. (2019), both the q-factor model (with four factors) and the q^5 model with expected growth (EG) factor is tested. In fact, the q^5 model also subsumes the Stambaugh and Yuan (2017) model. However, the objective of our paper is to test the original Hou et al. (2015) four-factor version (which was tested against the Fama-French four-factor version) against the Fama-French six-factor models. For this reason, parts of our results should be compared against Hou et al. (2019).

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stock market is still relatively small compared to the likes of Japan or China, as of 2019, the total market capitalization of the Stock Exchange of Thailand (SET) is around USD 570 billion, making it the 13th largest in the world and the second in Southeast Asia after Singapore.[2] Second, although Thailand is the second-largest financial market in Southeast Asia, it is the most liquid market in terms of trading volume in absolute dollar terms and relative to market capitalization. Third, companies listed in the Thai stock exchanges file quarterly financial reports aligned with reporting standards in the United States and Japan, permitting a like-for-like comparison in the factor performance not subject to differences in reporting regimes.

But despite its growing prominence, academic research on asset pricing factors and anomalies in Thailand remains limited. Extant research is based on the Fama and French (1993) three-factor model, augmented by the Amihud (2002) illiquidity factor (e.g., Puksamatanan, 2011; Pojanavatee, 2020) or the low beta factor (Saengchote, 2017). To the best of our knowledge, there is no published study on alternative asset pricing models, particularly with profitability and investment factors.

Beyond extending the q-factor tests, our study advances the strand of finance literature focusing on Asia-Pacific markets by rigorously testing and restricting the possible set of asset pricing models relevant to the region. A by-product of this replication study and the factors is a comprehensive list of asset pricing anomalies that have not been studied in detail. Empirical tests in Thailand are informative of broader asset pricing theories; as such, developing markets have typically been viewed as inefficient or more subject to behavioral biases (Chang et al., 2000; Morck et al., 2000). Finally, our research also sheds light on the applicability of q-factor constructions per Hou et al. (2015, 2019), which rely on quarterly financial data. Based on the fiscal year 2020 data on financial statements for 33 liquid markets globally, 21 have quarterly filings while 12 have semi-annual intra-year filings (many developed countries included).[3] This suggests that further replications and out-of-sample tests can be conducted for other markets as well.

2. Data & methodology

2.1. Data sources and sample construction

For the Thai sample, we use monthly equity data and quarterly/annual accounting data for firms in Thailand that are publicly listed in the Stock Exchange of Thailand (main market) and the Market for Alternative Investment (smaller firms) obtained from Refinitiv Datastream and WorldScope, and the Stock Exchange of Thailand. Due to data limitations to generate some anomaly portfolios, the sample period is between July 2000 and June 2019, covering 19 years and exactly 228 months. The sample includes both active and delisted firms, with the number of firms rising from approximately 300 to 700 over this period.

Following Schmidt et al. (2017) and Saengchote (2021), we drop observations with extreme returns. We also screen out "penny stocks" with low prices relative to tick size. Although tick sizes in Thailand are less than 1% of the stock price per tick on average, stocks with prices less than THB 1 move in THB 0.01 increments, magnifying their returns per tick movement. Consequently, we exclude stocks trading below THB 0.90 at the time of ranking. These penny stocks account for less than 1% of total trading volume on average.

We use the data libraries of Kenneth French and Hou et al. (2015) for the US sample, set to the same time span as our Thai sample.[4] This facilitates the comparability of results across the two countries while providing an out-of-sample extension for Hou et al. (2019).

To form portfolios, we use a combination of market-based data (such as market capitalization, returns, and trading volume) and accounting data (such as book value of equity, asset growth, and profitability). For the accounting data, Thailand follows the International Financial Reporting Standards (IFRS) but implements changes to the standards with a one-year lag whenever the IFRS are updated. Therefore, these values would also be comparable with those for other countries following similar standards.

2.2. Methodology

We test the performance of the q-factor model in comparison to the Fama-French six-factor model on a set of asset pricing anomalies using (i) factor spanning regressions of the long-short portfolios constructed from univariate sorts on asset pricing factors and (ii) pricing regressions of 6 (2 × 3 size-characteristics independent bivariate sorts) portfolios using the Gibbons et al. (1989) test.[5] For each portfolio *i*, we consider standard factor-spanning tests of the form:

$$r_{i,t} = \alpha_i + \sum_j \beta_j^i f_{j,t} + \varepsilon_{i,t}$$

[2] Comparison is made using data from the World Federation of Exchanges, accessible at https://focus.world-exchanges.org/issue/january-2020/market-statistics, last accessed August 7, 2021.

[3] Listed in alphabetical order, the markets which primarily report quarterly financial statements are: Austria, Canada, Denmark, Estonia, Finland, Germany, Hungary, India, Israel, Japan, Latvia, Malaysia, Mexico, Norway, Poland, Portugal, South Korea, Sweden, Taiwan (China), Thailand, and the United States. Countries which primarily report semi-annual financial statements include: Australia, Belgium, France, Hong Kong (China), Italy, the Netherlands, New Zealand, Singapore, Spain, Switzerland, and the United Kingdom. We note the summary above are based on the primary filing frequencies which the majority of firms conduct. Legally, some countries permit lower frequency reporting if a firm meets certain criteria. Therefore, in practice, not all firms in a country with quarterly primary reporting would have quarterly data.

[4] The data can be retrieved from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html and http://global-q.org/testingportfolios.html.

[5] For the US sample, we use 15 (3 × 5) portfolios for each asset pricing anomaly.

where $r_{i,\,t}$ is the test portfolio (e.g. candidate factor or long-short anomaly portfolio), $f_{j,\,t}$ is the factor premium and β_j^i is the factor loading of factor j of an asset pricing model on portfolio i.

Our portfolio spanning tests use the Barillas and Shanken (2017) tests as well as marginal contribution to maximum squared Sharpe ratio in Fama and French (2018). We evaluate asset pricing models based on (i) factor premia and statistical significance, and (ii) factor spanning regressions with respect to the other asset pricing model, the resulting adjusted R^2, and each factor's marginal contribution to a model's maximum squared Sharpe ratio, measured by the ratio of the squared intercept to the squared residual standard error (α^2/s^2).

We follow the factor construction methodologies of Fama and French (2018) and Hou et al. (2015, 2019) as closely as data allows. Details of the variable definitions are shown in the Appendix. The MKT factor is constructed as the value-weighted return of all stocks in both markets minus the one-month Treasury bill rate obtained from the Bank of Thailand. Fama-French factors are constructed by double-sorting (2×3 portfolios) annually to control for size, with a threshold determined by the 90% of total market capitalization, as recommended for non-US markets by Fama and French (2012). The HML factor sorts on size and the book-to-market ratio computed from the value of the book equity divided by market capitalization at December of the previous year; the RMW factor on size and operating profitability; the CMA factor on size and total asset growth; the SMB factor in this version controls for value, operating profitability and investment by first creating three sub-SMB factors that are double-sorted on size and the three variables, then the three sub-SMB factors are averaged as the overall SMB factor; the UMD factor is constructed monthly using market capitalization at the end of the ranking month and the cumulative 2–12 months' (skipping the most recent month's) prior returns. The Hou et al. (2015) q-factors are constructed using the $2 \times 3 \times 3$ sort on size, total asset growth, and return on equity.

For the test portfolios, Hou et al. (2015) started from a list of nearly 80 anomalies and found that only 35 are statistically significant. Because of data limitations in Thailand, we can only start with a list of 50 anomalies, which we narrow down to 15. Specifically, we construct long-short portfolios of 50 anomalies, which we classify using the same scheme (momentum, value/growth, investments, profitability, and trading friction) by constructing long-short spreads from 2×3 portfolio sorts on size and characteristics.[6] From the initial list of 50, we retain 15 anomalies whose spreads are statistically significant at the 5% level for further analyses. We keep the same anomalies as test assets for the US sample; consequently, the t-statistics for the Thai anomalies in Table 1 Panel B are necessarily greater than 1.96, while those of the US anomalies need not be.

3. Empirical results

Table 1 shows the summary statistics of the factors for both the US and Thailand. The average returns to the US q-factors in Panel A are smaller than those from Table 1 Panel A of Hou et al. (2019) with a sample between January 1967 and December 2016. The I/A and ROE factors in Thailand have average returns more than double those in the US over the same period with slightly higher standard deviations, resulting in higher Sharpe ratios. In Panel B, we report the average returns of the long-short spreads constructed from 2×3 sorts. Of the 15 statistically significant anomalies in Thailand, only 6 are statistically significant in the US, comprising earnings momentum (Abr-1, Abr-6), value (B/M), and profitability (ROA, ROE, NEI). More importantly, 6 anomalies that are significant in Hou et al. (2015) are no longer significant in this sample.

Taken together with the insignificant q-factor premia in Table 1 Panel A, the results in Panel B could be due to the crowding out of anomalies following publications and wider adoption of such strategies, as documented by McLean and Pontiff (2016) and Calluzzo et al. (2019). On the other hand, the more statistically and economically significant Thai premia compared to those in the US during the same period is consistent with the circumstances in Thailand where factor investing has not yet gained wide adoption.

Panel A of Table 2 shows the empirical results of the relationship between the q-factors and the Fama-French factors in the US. It is important to note that in Hou et al. (2015), the factor-spanning regressions were conducted with respect to the four-factor version, which has been subsequently expanded to include both profitability and investment in Fama and French (2018), so the comparison should be made to Hou et al. (2019) where the expanded Fama-French models are considered. Similar to Hou et al. (2019), ME is spanned by SMB. In this six-factor version, I/A and ROE are also spanned by CMA and RMW (and UMD), respectively, as reflected in their statistically insignificant intercepts, high adjusted R^2 and low a^2/s^2. This makes the q-factor model more comparable to the Fama-French model in this more recent sample than the timespan of Hou et al. (2019). On the other hand, the q-factor model is unable to explain the RMW factor. In Panel C, we find that the Fama-French model performs similarly to the q-factor model based on the number of unexplained anomalies represented by statistically significant alphas. The GRS test results also show similar evidence, with 10 statistically insignificant test statistics compared to 6.

Table 3 shows the main empirical results for Thailand. Like in the US, ME is also strongly related to SMB, I/A to CMA and ROE to RMW and UMD. However, unlike the US result, the ROE factor is not fully spanned by the Fama-French factors, with alpha of 0.93% per month and t-statistic of 5.10, suggesting that the q-factor model has potential to outperform the Fama-French model in Thailand. When evaluated against the 15 anomalies, the q-factor model reduces the t-statistics of the alphas for 13 out of 15 anomalies compared to the Fama-French model. In particular, the q-factor model performs better than the Fama-French model for momentum-related factors (S-Rev in Thailand has the opposite sign compared to theoretical prediction, making it more a short-term momentum than reversal), investment (NDF, OA) and profitability (ROA, ROE, NEI). Similar to the US result, the q-factor model is unable to price the book-to-market anomaly. The GRS test results also point to superior performance of the q-factor model, with 6 statistically insignificant

[6] While Hou et al. (2015) use long-short spreads constructed from univariate deciles, we use bivariate sorts to construct long-short spread to control for the potential influence of size on the anomaly. Consequently, for the US sample, the anomalies are constructed from 3×5 portfolios.

Table 1
Summary statistics of US replicated anomalies and Thai anomalies.

Panel A: Fama-French factors and q-factors

	Factors	United States				Thailand			
		Mean	SD	*t*	SR	Mean	SD	*t*	SR
Fama-French	MKT	0.47	4.37	1.63	0.11	1.04	6.08	2.59	0.17
	SMB	0.27	2.58	1.60	0.11	0.13	3.78	0.51	0.03
	HML	0.23	2.94	1.19	0.08	0.70	2.89	3.63	0.24
	RMW	0.47	2.49	2.83	0.19	0.19	3.26	0.90	0.06
	CMA	0.27	2.03	2.02	0.13	0.39	2.89	2.04	0.14
	UMD	0.14	5.06	0.43	0.03	0.81	5.52	2.22	0.15
q-Factors	ME	0.31	2.61	1.82	0.12	0.25	3.64	1.04	0.07
	I/A	0.22	1.96	1.71	0.11	0.45	2.85	2.40	0.16
	ROE	0.34	2.88	1.78	0.12	1.10	3.34	4.97	0.33

Panel B: Test anomalies

	Anomaly	United States				Thailand			
		Mean	SD	*t*	SR	Mean	SD	*t*	SR
Momentum	Abr-1	0.43	1.82	3.58	0.24	1.30	2.68	7.35	0.49
	Abr-6	0.25	1.33	2.89	0.19	0.74	1.90	5.93	0.39
	R6-1	0.23	4.46	0.79	0.05	0.77	4.68	2.50	0.17
	R11-1	0.17	5.95	0.44	0.03	0.86	5.54	2.34	0.15
Value/Growth	B/M	0.58	3.48	2.50	0.17	0.70	2.89	3.65	0.24
	E/P	0.32	2.54	1.90	0.13	0.64	3.70	2.60	0.17
	CF/P	0.35	3.10	1.69	0.11	0.64	3.66	2.63	0.17
	D/P	0.12	2.74	0.68	0.04	0.66	4.74	2.10	0.14
Investments	I/A	0.17	1.74	1.52	0.10	0.40	2.89	2.07	0.14
	NDF	0.14	1.28	1.63	0.11	0.44	2.26	2.96	0.20
	OA	0.01	1.76	0.08	0.01	0.56	2.50	3.39	0.22
Profitability	ROA	0.66	3.85	2.57	0.17	0.87	2.71	4.86	0.32
	ROE	0.76	3.84	2.98	0.20	1.07	2.89	5.57	0.37
	NEI	0.50	2.37	3.18	0.21	0.72	3.83	2.83	0.19
Trading friction	S-Rev	0.40	4.18	1.45	0.10	−0.94	4.58	3.09	−0.20

This table reports the summary statistics from January 2000 to June 2019 with 228 months of data. The US Fama-French factors are obtained from Kenneth French's website, while the q-factors and anomalies are obtained from Hou-Xue-Zhang's global-q.org website. For the construction of Fama-French factors, at the end of June in each year, stocks are divided into large-cap and small-cap stocks using a threshold where large-cap stocks represent 90% of market capitalization as recommended by Fama and French (2012). For other characteristics (book-to-market ratio, operating profitability, and asset growth), stocks are divided into 3 groups based on the 30th and 70th percentiles. Monthly value-weighted returns on the 6 size-characteristics sorted portfolios are calculated and form the bases for the high-minus-low (book-to-market, HML; operating profitability, RMW) or low-minus-high (asset growth, CMA) factors. For the construction of q-factors, the definition of profitability used is the return on equity (ROE), which is computed using quarterly net income before extra/preferred dividend and book equity. Stocks are independently sorted on size (ME), ROE, and asset growth (I/A) into 18 portfolios which are rebalanced monthly. The size factor (ME) is the low-minus-high difference between the 9 small portfolios and 9 big portfolios. The investment factor (I/A) is the low-minus-high difference between the 6 low I/A portfolios and 6 high I/A portfolios. The ROE factor is the high-minus-low difference between the 6 high ROE portfolios and 6 low ROE portfolios. The anomalies are constructed from independent sorting on size and characteristics (6 portfolios) using 30th and 70th percentiles as cut-offs and reported as long-short spreads. Average returns, standard deviations, and Sharpe ratios are all presented as monthly returns.

test statistics compared to 3 for the Fama-French model. With this evidence, we conclude that the q-factor model performs better in Thailand.

4. Conclusion

Using an appropriate asset pricing model is important for both industry-related benchmarking results as well as academic research. This paper compares the relative performance of the Fama-French six-factor model with the q-factor model in Thailand. Our replication of the US data yields somewhat different results from Hou et al. (2019) due to differences in the timeframe. However, the performance of the q-factor model remains comparable to the Fama-French six-factor model. For Thailand, on the other hand, the q-factor model is superior on many dimensions despite having four factors. Overall, our results highlight the academic need to re-examine the empirical results in non-US markets as well as in the US with different timeframes, as the choice of an appropriate asset pricing model may change over time given the evolving behavior of market participants, as evidenced by McLean and Pontiff (2016) and Calluzzo et al. (2019).

Table 2
Pricing errors and tests of overall performance: replication of the United States.

Panel A: Explaining the q-factors

	Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}	A. R^2	α^2/s^2
ME	0.31	0.02	0.02	0.95	0.12	0.02	−0.04		0.93	0.001
	(1.82)	(0.43)	(1.64)	(51.5)	(5.79)	(0.93)	(1.32)			
		0.02	0.03	0.95	0.14	−0.00	−0.05	0.04	0.94	0.001
		(0.43)	(2.80)	(53.7)	(6.90)	(0.11)	(1.20)	(4.73)		
I/A	0.22	−0.02	−0.00	0.01	0.05	0.01	0.86		0.87	0.001
	(1.71)	(0.50)	(0.33)	(0.51)	(2.08)	(0.25)	(27.9)			
		−0.02	−0.01	0.01	0.04	0.01	0.86	−0.01	0.87	0.001
		(0.50)	(0.45)	(0.54)	(1.91)	(0.38)	(27.7)	(−0.60)		
ROE	0.34	0.14	−0.15	−0.15	−0.08	0.67	0.04		0.59	0.006
	(1.78)	(1.10)	(4.17)	(2.81)	(1.45)	(10.5)	(0.47)			
		0.14	−0.06	−0.17	0.029	0.53	−0.06	0.26	0.76	0.010
		(1.37)	(2.30)	(4.10)	(0.64)	(10.5)	(1.01)	(12.2)		

Panel B: Explaining the Fama-French factors

	Mean	α	β_{MKT}	β_{ME}	$\beta_{I/A}$	β_{ROE}	A. R^2	α^2/s^2
SMB	0.27	0.07	−0.06	0.94	−0.05	−0.16	0.947	0.015
	1.60	(1.74)	(5.28)	(57.3)	(2.24)	(9.39)		
HML	0.23	−0.09	0.05	0.22	0.91	0.08	0.430	0.002
	1.19	(0.58)	(1.21)	(3.59)	(11.5)	(1.18)		
RMW	0.47	0.32	−0.09	−0.05	0.22	0.51	0.571	0.035
	2.83	(2.70)	(2.74)	(1.22)	(3.71)	(10.8)		
CMA	0.27	0.06	−0.01	0.00	0.96	0.01	0.870	0.008
	2.02	(1.25)	(0.84)	(0.00)	(36.7)	(0.26)		
UMD	0.14	−0.27	−0.08	0.22	−0.11	1.21	0.481	0.006
	0.43	(1.08)	(1.15)	(2.22)	(0.85)	(11.5)		

Panel C: Test portfolios results for Fama-French and q-factors

	Abr-1	Abr-6	R6–1	R11–1	B/M	E/P	CF/P	D/P	I/A	NDF	OA	ROA	ROE	NEI	S-Rev
m	0.43	0.25	0.36	0.17	0.58	0.32	0.35	0.12	0.17	0.14	0.01	0.66	0.76	0.50	0.40
α_{FF}	0.43	0.21	0.13	0.00	0.18	−0.03	−0.14	0.06	0.15	0.05	0.07	0.31	0.36	0.32	0.45
α_q	0.39	0.15	−0.17	−0.39	0.40	0.13	0.10	0.17	0.05	0.02	0.11	0.22	0.27	0.20	0.41
t_m	3.58	2.89	0.91	0.44	2.50	1.90	1.69	0.68	1.52	1.63	0.08	2.57	2.98	3.18	1.45
t_{FF}	3.94	2.88	0.67	0.05	1.48	0.32	1.10	0.40	1.53	0.60	0.69	2.24	2.61	2.61	1.70
t_q	3.40	1.89	0.58	1.35	2.28	0.86	0.55	1.11	0.50	0.23	1.05	2.35	2.98	2.11	1.55
p_{FF}	0.00	0.00	0.26	0.26	0.08	0.63	0.66	0.22	0.24	0.74	0.79	0.00	0.00	0.00	0.05
p_q	0.00	0.00	0.02	0.01	0.01	0.34	0.40	0.29	0.07	0.71	0.24	0.00	0.00	0.00	0.01

This table replicates Table 1 (Panel A) of Hou et al. (2019) and Table 4 (Panel B) of Hou et al. (2015) using data from July 2000 to June 2019 for ease of comparability. Panel A shows the results of factor spanning regressions of q-factors on Fama-French models, and panel B shows the results of factor spanning regressions of Fama-French factors on the q-factor model. Maximal contribution to the Sharpe ratio proposed by Barillas and Shanken (2017) is calculated as the ratio between the square of the intercept and the square of the residual standard errors. Panel C shows the average return (m) of each asset pricing anomaly and the spanning regression alpha (α) with respect to different asset pricing models (Fama-French six-factor and q-factor) and the associated t-statistics (t_m, t_{FF}, t_q) of the average returns, Fama-French six-factor alpha and q-factor alpha respectively. p_{FF} and p_q are the *p*-values of the GRS test on the null hypothesis that the alphas of the portfolios formed on each of the variables are jointly zero. Returns are represented in percentage points, and absolute values of *t*-statistics are reported in parentheses under the point estimates in Panel A and B.

Table 3
Pricing errors and tests of overall performance: Thailand.

Panel A: Explaining the q-factors

	Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}	A. R^2	α^2/s^2
ME	0.25	0.20	−0.03	0.90	−0.03	−0.02	−0.02		0.92	0.036
	(1.04)	(2.66)	(2.22)	(41.4)	(1.26)	(0.75)	(0.63)			
		0.12	−0.03	0.90	−0.03	−0.02	−0.02	0.00	0.91	0.035
		(2.60)	(2.15)	(40.8)	(1.30)	(0.80)	(0.68)	(0.35)		
I/A	0.45	0.03	0.00	0.04	0.10	0.08	0.84		0.72	0.000
	(2.40)	(0.28)	(0.19)	(1.27)	(2.82)	(2.25)	(21.2)			
		0.00	0.01	0.03	0.09	0.07	0.83	0.04	0.73	0.000
		(0.06)	(0.48)	(0.92)	(2.54)	(1.86)	(20.8)	(2.15)		
ROE	1.10	1.09	−0.11	0.00	−0.02	0.44	0.13		0.22	0.139
	(4.97)	(5.23)	(2.92)	(0.04)	(0.32)	(6.34)	(1.71)			
		0.93	−0.07	−0.07	−0.09	0.35	0.05	0.28	0.40	0.135
		(5.10)	(2.17)	(1.30)	(1.45)	(5.67)	(0.69)	(8.37)		

Panel B: Explaining the Fama-French factors

	Mean	α	β_{MKT}	β_{ME}	$\beta_{I/A}$	β_{ROE}	A. R^2	α^2/s^2
SMB	0.13	0.02	−0.02	0.98	0.04	−0.12	0.92	0.000
	(0.51)	(0.20)	(−1.38)	(45.8)	(1.72)	(5.63)		
HML	0.70	0.57	0.06	0.06	0.34	−0.09	0.12	0.044
	(3.63)	(2.86)	(1.68)	(1.13)	(5.33)	(1.61)		
RMW	0.19	0.05	−0.10	−0.23	−0.38	0.44	0.35	0.000
	(0.90)	(0.25)	(2.93)	(4.25)	(6.13)	(7.93)		
CMA	0.39	0.20	−0.03	−0.01	0.88	−0.16	0.74	0.018
	(2.04)	(1.82)	(1.38)	(0.31)	(25.1)	(5.13)		
UMD	0.81	−0.14	−0.05	0.20	0.29	0.75	0.30	0.001
	(2.22)	(0.41)	(0.89)	(2.07)	(2.61)	(7.78)		

Panel C: Test Portfolios Results for Fama-French and q-factors

	Abr-1	Abr-6	R6–1	R11–1	B/M	E/P	CF/P	D/P	I/A	NDF	OA	ROA	ROE	NEI	S-Rev
m	1.30	0.74	0.77	0.86	0.70	0.64	0.64	0.66	0.40	0.44	0.56	0.87	1.07	0.72	−0.94
α_{FF}	1.24	0.72	0.35	0.04	0.00	0.42	0.44	0.99	0.01	0.29	0.54	0.96	1.13	0.59	−0.62
α_q	1.15	0.69	0.22	−0.12	0.57	0.43	0.44	0.72	0.20	0.29	0.55	0.49	0.33	0.46	−0.50
t_m	7.35	5.93	2.50	2.34	3.65	2.60	2.63	2.10	2.07	2.96	3.39	4.86	5.57	2.83	3.09
t_{FF}	6.92	5.82	1.77	1.62	2.21	2.31	2.40	4.15	1.37	2.14	3.19	5.43	6.18	2.68	2.02
t_q	5.97	5.18	0.71	0.34	2.86	1.88	1.96	2.93	1.84	1.86	3.09	2.99	2.72	1.92	1.55
p_{FF}	0.00	0.00	0.01	0.22	0.00	0.03	0.02	0.00	0.05	0.06	0.00	0.00	0.00	0.17	0.01
p_q	0.00	0.00	0.02	0.18	0.03	0.09	0.08	0.10	0.02	0.09	0.00	0.00	0.00	0.27	0.01

This table reports the factor spanning regressions using Thai data from July 2000 to June 2019. Panel A shows the results of factor spanning regressions of q-factors on Fama-French models and panel B shows the results of factor spanning regressions of Fama-French factors on the q-factor model. Maximal contribution to the Sharpe ratio proposed by Barillas and Shanken (2017) is calculated as the ratio between the square of the intercept and the square of the residual standard errors. Panel C shows the average return (m) of each asset pricing anomaly and the spanning regression alpha (α) with respect to different asset pricing models (Fama-French six-factor and q-factor) and the associated t-statistics (t_m, t_{FF}, t_q) of the average returns, Fama-French six-factor alpha and q-factor alpha respectively. p_{FF} and p_q are the p-values of the GRS test on the null hypothesis that the alphas of the portfolios formed on each of the variables are jointly zero. Returns are represented in percentage points, and absolute values of t-statistics are reported in parentheses under the point estimates in Panel A and B.

Appendix A. PBFJ replication study master pitch template

Pitcher team names	JEL Code G12, G14 Date Completed March 5, 2021
(A) Working Title	Digesting anomalies: a q-factor approach for the Thai Market
(B) Basic Research Question	Can the investment CAPM q-factor model better explain equity returns than the Fama-French model in Thailand?
(C) Key paper(s)	*Target replication paper*: Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. The Review of Financial Studies, 28(3), 650–705. *Key papers*: Barillas, F., & Shanken, J. (2017). Which alpha?. The Review of Financial Studies, 30(4), 1316–1338. Fama, E. F., & French, K. R. (2018). Choosing factors. Journal of Financial Economics, 128(2), 234–252.
(D) Motivation/Puzzle	The key innovation of Hou et al. (2015) was the introduction of a theoretically driven factor model which at least matched or out-performed the Fama-French three-factor or four-factor model. However, while the Fama and French three to five factor framework has been tested in emerging markets, the investment capital asset pricing model-based factors per Hou et al. (2015) have not been tested. We seek to study whether similar conclusions apply out of sample, paying particular attention to the institutional detail in Thailand in terms of accounting regimes and reporting frequencies.
THREE	Three core aspects of any empirical research
(E) Idea?	The core idea behind this study is that the q-factor asset pricing model that includes profitability and investment factors can better explain equity returns than the Fama-French model. We extend the evidence in Table 4 of Hou et al. (2015) to the Thai stock market.
(F) Data?	We use monthly equity data and quarterly/annual accounting data for firms in Thailand that list in the Stock Exchange of Thailand (main market) and the Market for Alternative Investment (for smaller firms) between July 2000 and June 2019 (19 years) with data retrieved from Refinitiv Datastream, WorldScope, and Eikon. The number of firms rise from approximately 300 to 700 over this period. To form portfolios, we use a combination of market-based data (such as market capitalization, returns and trading volume) and accounting data (such as book value of equity, asset growth, and profitability). We use information for stocks listed, allowing those which later failed (so the sample is survivorship-free) in all equity markets in Thailand. Therefore, we do not anticipate selection bias. However, the asset pricing anomalies chosen for this study may differ from the U.S. setting due to (i) data availability to construct sorting variables and (ii) different setting. Given the lack of academic research on anomalies in Thailand, we first establish a list of statistically significant anomalies and then base our analysis of asset pricing models on them.
(G) Tools?	We apply an algorithm to clean data for potential errors, handle outliers, and exclude "penny stocks" and other illiquid non-tradable stocks when forming portfolios. We will construct the q-factors following the methodology of Hou et al. (2015), namely using portfolio sorts and then use the Barillas and Shanken (2017) tests as well as marginal contribution to maximum squared Sharpe ratio in Fama and French (2018), to examine (i) factor premia and statistical significance, and (ii) factor spanning regressions with respect to the Fama and French (2018) six-factor model (with momentum). We also will also test the performance of the q-factor model in comparison to the six-factor model on a set of asset pricing anomalies using (i) factor spanning regressions of the long-short portfolios constructed from univariate sorts on asset pricing factors and (ii) pricing regressions of 6 (2×3 size-characteristics independent bivariate sorts) portfolios. Stata will be used to perform the analyses.
TWO	Two key questions
(H) What's New?	We apply similar factor construction methodologies as the original papers, extending it to a new country with different institutional settings, and evaluates it performance relative to the extended version of the Fama-French model using more updated empirical tests.
(I) So What?	The extension of the Hou et al. (2015) analysis will provide additional out-of-sample tests which extend the theoretically driven q-factor. As part of a paradigm shift, we believe such rigorous out-of-sample testing is important to advance the consensus asset pricing model. For practice, the asset management industry can learn more about new portfolio constructions which may result in more robust portfolios with more stable returns.
ONE	One bottom line
(J) Contribution?	Beyond just extending the q-factor tests, our study advances the strand of finance literature focusing on Asia-Pacific markets by rigorously testing and restricting the possible set of asset pricing models that are relevant for the region. The byproduct of this replication study in addition to the factors is a list of asset pricing anomalies which has so far been little studied.
(K) Other considerations	Data availability is the key consideration for this project. Some anomalies cannot be studied because underlying data is not available, but all the data required for the asset pricing factors are available. The overall completion risk of this project is low.

Appendix B. Supplementary data

Here, we discuss the procedures to construct asset pricing factors and test portfolios. For annually sorted portfolios, financial statements data as of end of December are used for sorting in June of the following year to ensure data is available to investors on the sorting date. Similarly, quarterly financial statement items are lagged by one quarter. All returns in the factor and test portfolio construction are total returns inclusive of dividend payments. We discuss the variable definitions used for factor construction below, with WorldScope data codes in parentheses where applicable.

Fama-French factors

Book equity for the HML factor is computed as the sum of common shareholders' equity (WC03501) and preferred stock (WC03451) when available, otherwise it is total assets (WC02999) minus total liabilities (WC03351). To calculate the book-to-market ratio, we use the end-of-year value of the book equity divided by market cap in December of the same year. Operating profitability for the RMW factor is computed as sale (WC01001) minus cost of goods sold (WC01051), selling, general, and administrative expenses (WC01101), and interest (WC01251), divided by lagged book equity. Asset growth for the CMA factor is computed from annual changes total assets (WC02999).

q-factors

The q-factors require computation from quarterly data which have the same data item code as earlier with suffix A. For example, the I/A factor uses asset growth like the CMA factor but uses WC02999A instead of WC02999. For the ROE factor, the definition of profitability is slightly different from the RMW factor, as the numerator used is net income before extra/preferred dividend (WC01551A) and denominator is one-quarter lagged book equity.

Test portfolios

Abr-1, Abr-6. Abnormal returns around quarterly earnings announcement date. For each announcement date, we compute the abnormal returns over the value-weighted market portfolio over a 4-day window (from one day before announcement to two days after). Abr_i is sorted monthly, and stocks whose most recent announcement dates are more than 6 months old are removed from the sample.

$$Abr_i = \sum_{d=-2}^{+1} r_{i,d} - r_{m,d}$$

Abr-1 portfolios are formed with 1-month holding period, while Abr-6 portfolios are formed with 6-month holding period. That is, in each month, there are 6 sub-portfolios which are formed at different points in time. The returns of the 6 sub-portfolios are then equally-weighted to form the test portfolio.

R6-1, R11-1. Momentum; specifically, Rj-1 are momentum portfolios formed on past j-month cumulative returns and 1-month holding periods. Portfolios are formed monthly.

B/M. Book-to-market ratio, defined earlier.

E/P. Earnings-to-price ratio, computed as net income (WC01751) divided by market capitalization at December of the same year. E/P is sorted annually.

CF/P. Cashflow-to-price ratio, computed as net income (WC01751) plus depreciation and amortization (WC01151) divided by market capitalization at December of the same year. CF/P is sorted annually.

D/P. Dividend-to-price ratio, sorted on dividend yield (DY) at the end of June. D/P is sorted annually.

I/A. Investment-to-asset ratio, computed from annual changes total assets (WC02999). I/A is sorted annually.

NDF. Net debt financing, computed as change in total debt (WC03255), scaled by average total assets (WC02999). NDF is sorted annually.

OA. Operating accruals, computed as annual change in operating assets, which is defined as current assets (WC02201) less cash and short-term investments (WC02001), minus change in operating liabilities, which is defined as current liabilities (WC03101) less short-term debt and current portion of long-term debt (WC03051), minus depreciation and amortization (WC01151), scaled by lagged total assets (WC02999). OA is sorted annually.

ROA. Return on assets, computed as net income before extra/preferred dividend (WC01551A) divided by lagged total assets (WC02999A). ROA is sorted quarterly.

ROE. Return on equity, computed as net income before extra/preferred dividend (WC01551A) divided by lagged book equity (defined earlier). ROE is sorted quarterly.

NEI. Number of consecutive quarters with an increase in earnings, counted from quarterly net income before extra/preferred dividend (WC01551A), up to 8 quarters. NEI is sorted quarterly.

S-Rev. Short-term reversal, ranked based on one-month return with one-month holding period. Portfolios are formed monthly.

Code to replicate our empirical results and the data files are available online. Additional details on factor construction are available from Saengchote (2021).

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