Are value premiums driven by behavioral factors?

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ABSTRACT

This study investigates the role of behavioral factors in driving value premiums in the Thai stock market. Using data from July 2001 to September 2024, we assess eight value premium definitions against fundamental-based models, including the Fama-French six-factor and q-factor models. While these models explain much of the premiums, they fail to fully account for strategies like the dividend-to-price (DP) portfolio. Augmenting the models with behavioral factors—post-earnings-announcement drift (PEAD) and net equity issuance (FIN)—improves their explanatory power, indicating that behavioral biases contribute to value premium persistence in Thailand. The continued significance of the DP portfolio also suggests that corporate governance factors influence asset pricing anomalies. These findings underscore the importance of integrating risk, behavioral, and corporate governance considerations to explain value premiums.

Keywords: value investing, behavioral finance, asset pricing models, post-earnings-announcement drift, corporate governance

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1. Introduction

Value investing, often credited to the seminal 1934 book by Benjamin Graham and David Dodd, *Security Analysis*, is about finding price-intrinsic value discrepancies in the market. It is often done by comparing some accounting fundamentals, such as the stock of productive capital or flows of profits and dividends to market price as a ratio, and “value stocks” (or “cheap” stocks) would correspond to stocks with high values of such ratio. Since the 1970s, researchers have documented strong, systematic relationships between various price-based ratios and future stock returns, for example, the earnings-to-price ratio (Basu, 1977), the dividend-to-price ratio (Litzenberger and Ramaswamy, 1979), the sale-to-price ratio (Barbee, Mukherji, and Raines, 1996), and the return spread between a portfolio of stocks with high values of such ratio compared to a portfolio of stocks with low values is often referred to as the “value premium.”

The premium is found in equity and many other asset classes, as documented by Asness, Moskowitz, and Pedersen (2013). Because of the prevalence and persistence, Fama and French (1993, 2015, 2018) formalize this characteristic as a pricing factor in their asset pricing model, along with market risk exposure, size, profitability, investment, and momentum. Over time, as more characteristics are added to asset pricing models, the Fama-French value factor constructed from the book-to-market ratio appears to be subsumed by other factors. The influential paper by Novy-Marx (2013) that documents the role of gross profitability on the value premium precedes the findings of Fama and French (2015) that the value factor is spanned by the other factors of the five-factor model, similar to the Hou, Xue, and Zhang (2015) q-factor model that does not contain the value factor and can explain the Fama-French value premium. In addition, there are accounts of how the traditional value premium has diminished in recent years (Fama and French, 2021), leading to discussions about how value premium should be defined and alternative definitions that still earn systematic returns (e.g., Israel, Laursen, and Richardson, 2020; Blitz and Hanauer, 2020; Arnott et al., 2021).

However, beyond this empirical evidence, there is still a general disagreement among researchers about why such a premium exists. On the one hand, the value premium can be viewed as a risk premium where investors are compensated for taking on systematic risk (Fama and French, 1993), while on the other hand, it could be an over/underreaction to information that causes temporary mispricing (Lakonishok, Schleifer, and Vishny, 1994; Daniel, Hirshleifer, and

Subrahmanyam, 1997), implying that markets are inefficient (Basu, 1977; Rosenberg, Reid, and Landstein, 1985).

Traditional models like the Fama-French six-factor and q-factor models rely on fundamental risk factors such as size, value, profitability, investment, and momentum. While these models capture variability in stock returns, they fail to account for certain anomalies, especially in emerging markets like Thailand. Behavioral biases and governance factors, which are prevalent in less mature markets, remain unaddressed in these models. The Thai market exhibits different investor behavior patterns and regulatory environments, making traditional models incomplete in explaining all anomalies.

Our research makes two important contributions. First, we provide evidence on eight alternative definitions of value premiums in Thailand. We find that the Fama-French six-factor and q-factor models do not fully price the eight versions of the value premium. Second, in attempting to shed light on the potential sources of the premium in Thailand, we contribute to the ongoing discussion on whether behavioral factors drive the value premium. We summarize these behavioral factors into two factors similar to those of Daniel, Hirshleifer, and Sun (2020). The model better explains value premiums by augmenting the Fama-French and q-factor models with these two behavioral factors. However, these augmented models cannot explain the dividend-to-price (DP).

The rest of this paper is organized as follows. In the next section, we review how the value factor is viewed in the context of commonly used asset pricing models and potential behavioral factors that could influence asset prices. In Section 3, we describe the data, the construction methodology of the asset pricing and behavioral factors, and the statistical test that will be used to assess the contribution of behavioral factors. Section 4 reports the results, and we conclude in Section 5.

2. Literature Review

2.1 Asset Pricing Models and the Value Factor

The most prominent asset models that incorporate these two aspects employed by academic research are the Fama and French (2015, 2018) model, which is based on the dividend discount valuation of Modigliani and Miller (1961), and the Hou et al. (2015) q-factor model, which is based on a quadratic adjustment cost investment model of Cochrane (1991) and derives its name from the Tobin's q in the fashion of Hayashi (1982).

The theoretical framework for the factors provided by Fama and French (2015) has three direct implications: holding all other components of the model constant, (1) lower book-to-market ratio (HML), (2) higher profitability, (RMW), and (3) lower investment (CMA) imply higher expected stock returns. For the Hou et al. (2015) q-factor model, the first-order conditions of the firm's investment problem and household's consumption-based stochastic discount factor give rise to an equation that implies a firm's return should be (1) positively related to profitability (ROE) and (2) negatively related to its investment-to-asset ratio (I/A). In short, the empirical predictions are essentially the same as those of Fama and French (2015), but the motivating theories are different. Unlike the Fama-French model, the q-factor model does not contain any value-like factor (e.g., price-to-earnings ratio or book-to-market ratio) as the theoretical model does not need this variable.

Hou et al. (2015) demonstrate that the q-factor model containing market risk (MKT), size (ME), profitability (ROE), and investment (I/A) can explain more than half of 80 documented anomalies and outperforms the Fama-French (1993) 3-factor model and the Carhart (1997) 4-factor model. In its construction, the investment factor is computed from changes in total assets, like Fama and French (2015).[1] The authors explain their choice of proxy by stating that "asset growth is the most comprehensive measure of investment-to-assets." In the factor spanning regression, the ME and I/A factors are highly correlated with HML, and the q-factor model prices the portfolios sorted on book-to-market ratio well. Fama and French (2015) also concede that by adding profitability and investment factors, the value factor defined by Fama and French (1993) becomes redundant, but they still opt to include HML in their model.

2.2 Behavioral Explanations

The Fama-French and q-factor models are often viewed as "rational" factors because they arise from some decisions of rational agents. However, at their core, statistical factors models

[1] In their implementation, Fama and French (2015) construct the investment factor based on total asset growth rather than book equity growth. For levered firms or firms with liabilities, the two growth rates are not the same. The authors do not explain the rationale behind this definition, but it is worth noting that the empirical results with respect to investment tend to be based on assets. Nevertheless, there is no unified definition in the literature; for example, Titman, Wei and Xie (2004) use average capital expenditure to sales, while Thomas and Zhang (2002) use change in inventory to total assets.

comprise common characteristics of assets that can predict future returns reliably and persistently. For example, the momentum factor lacks fundamental motivation, but its pervasiveness in many markets (even in asset classes other than equity) leads to its eventual adoption in many asset pricing models. Fama and French (2018) lament – as they finally include momentum as the sixth factor in their model – that "we worry, however, that opening the game to factors that seem empirically robust but lack theoretical motivation has a destructive downside: the end of discipline that produces parsimonious models and the beginning of a dark age of data dredging that produces a long list of factors with little hope of sifting through them in a statistically reliable way."

These fundamental models often assume that agents are rational and the market is efficient and in equilibrium, so the market price reflects the asset's fundamental value. However, it is also possible that these assumptions do not hold, and some market imperfections or behavioral biases can lead to systematic "mispricing" or "anomalies." Several studies, such as Stambaugh and Yuan (2017), Weber (2018), Thampanya et al. (2020), and Pornpikul and Nettayanun (2022), have documented the influence of these behavioral factors on returns. Researchers typically define factors in two ways: macro factors, which are based on observable states of the world (for example, Thampanya et al., 2020), and mimicking portfolios, which are constructed from portfolios of assets with certain characteristics (for example, Stambaugh and Yuan, 2017; Daniel, Hirshleifer and Sun, 2020; Pornpikul and Nettayanun, 2022).

Since the first publication of *Security Analysis*[2] in 1934 and *The Intelligent Investor*[3] in 1949, the rationales used by investors to justify the value premium have the essence of both fundamental and behavioral factors. For example, the term "margin of safety" — well-known in the value investing community — describes how value investors can take advantage when a security's price is less than its intrinsic value. "Mr. Market" is another notion that investors should not be moved by behavioral trading in the market. Mr. Market is viewed as an agent who bids and offers, and investors should buy stocks when Mr. Market offers a discounted price. Both these terms point to opportunities in the market where prices differ from their fundamental values.

Based on these observations, periods when stock prices systematically deviate from their fundamental values (i.e., mispriced) can influence the value premium. Investors can take a long position in undervalued stocks and a short position in overvalued stocks, and the returns difference

[2] See Graham and Dodd (2004).
[3] See Graham, Zweig, and Buffett (2006).

would be statistically significant. Researchers studied several forms of mispricing which are often related to behavioral biases: for example, loss aversion (Kahneman and Tversky, 1979), overreaction (Jegadeesh and Titman, 1993; Hirshleifer and Subrahmanyam, 1998), overconfidence represented by high accrual stocks (Sloan, 1996), limited arbitrage (Shleifer and Vishny, 1997), limited attention for accounting report (Hirshleifer et al., 2004), overconfidence represented by asset growth (Shiller, 2005; Cooper, Gulen and Schill, 2008), market sentiment (Baker and Wurgler, 2006, 2007; De Long et al., 1990), trading volume (Baker and Wugler, 2007), and underreaction to the current profitability (Wang and Yu, 2013).

Recognizing the systematic influence of behavioral factors on asset prices, several researchers have directly incorporated behavioral factors constructed as mimicking portfolios into asset pricing models. For example, using a statistical clustering technique, Stambaugh and Yuan (2017) propose a four-factor model with two mispricing factors constructed from 11 asset pricing anomalies. The new four-factor model can outperform the Hou, Xue, and Zhang (2015) q-factor model and the Fama-French (2015) five-factor model. Daniel, Hirshleifer, and Sun (2020) also construct two behavioral factors, but rather than using the 11 anomalies, the post-earnings-announcement drift factor is used to represent the short-term mispricing, and the net equity issuance factor is used to represent the long-term mispricing. By combining these two behavioral factors with the market factor, the researchers show that the three-factor model can explain most anomalies in the stock market.

In this study, we construct behavioral factors as mimicking portfolios and follow Daniel, Hirshleifer, and Sun (2020) as not all 11 anomalies used by Stambaugh and Yuan (2017) are available in the Thai market, and because the factor construction methodology of Daniel, Hirshleifer and Sun (2020) is more accessible and hence tradable. We analyze the eight versions of the value premium with the three-factor model with behavioral factors and later show that augmenting the Fama-French six-factor model and the q-factor model with the two behavioral factors can better explain the value premium.

1. Data and Empirical Methodology

3.1 Pricing Factor Construction

To construct asset pricing factors, we use the Stock Exchange of Thailand's SETSMART database to retrieve prices, returns, and financial statements of all stocks listed in Thailand, active and inactive. We do not make a distinction between stocks listed on the main board, the Stock

Exchange of Thailand (SET), and the alternative board, the Market for Alternative Investment (mai), and consider them jointly as the "market." Exchange-traded funds are excluded from the sample, but we include property funds and REITs because their holdings are not listed stocks, making them a distinct asset class rather than a pass-through vehicle in defining the market. We retrieve market and accounting data to construct factors from July 2001 to September 2024. Following Schmidt et al. (2017), we drop observations with extreme returns and, in addition, screen out "penny stocks" with low prices. Definitions of penny stocks vary, but the idea is to screen out stocks with mechanically extreme price movements. To pick the cutoff, we appeal to the tick size. The tick size in Thailand is usually less than 1% per tick, but 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. To ensure liquidity, we also require that stocks be ranked into portfolios and traded consecutively for at least three months before the ranking date.

We follow the factor construction methodologies of Fama and French (2018) and Hou et al. (2015) as closely as data allows. Specifically, the MKT factor is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate obtained from the Bank of Thailand. The SMB, HML, RMW, and CMA factors are constructed based on rankings conducted at the end of June using financial statements from the previous year (December). All Fama-French factors are constructed by double-sorting (2×3 portfolios) to control for size and formed at the end of June. The size breakpoint is defined to classify the stocks comprising 90 percent of total market capitalization as large, while the breakpoints for the three portfolios are defined based on the 30th and 70th percentile. The HML factor sorts on size and the book-to-market ratio computed from the book equity value divided by market cap at the end of December of the previous year, the RMW factor on size and operating profitability, and the CMA factor on size and total asset growth. The SMB factor in this version controls value, operating profitability, and investment by first creating three sub-SMB factors double-sorted by size and the three variables. Then, the three sub-SMB factors are averaged as the overall SMB factor. On the other hand, the UMD factor is constructed monthly using the market cap at the end of the ranking month and the cumulative 2-12 months (11 months, skipping the most recent month) returns.

The q-factor model is constructed from a tri-variate size, quarterly ROE, and quarterly total asset growth (2×3×3 portfolios). The 18 value-weighted portfolios are combined with equal weights to construct the ME, I/A, and ROE factors. The q-factor model does not include the momentum factor since the other factors span it.

When available, book equity is computed as the sum of common shareholders' equity (M_SHLD_EQUITY) and preferred stock (M_PREFERRED_SHARES). Otherwise, it is computed as total assets (M_TOTAL_ASSET) minus total liabilities (M_TOTAL_LIABILITY). The RMW factor is constructed at the end of June using operating profitability from the previous year's financial statements computed as sales (M_ACC_SALE) minus the cost of goods sold (M_ACC_COS), selling, general, and administrative expenses (M_ACC_SELLING_ADMIN), and interest (M_ACC_INT_EXPENSE), divided by lagged book equity. The CMA factor is constructed from the change in total assets divided by one-quarter lagged total assets, and the same variable is used for the q-factor's I/A.

The q-factor quarterly ROE computation slightly differs from the Fama-French definition regarding frequency and profit. The numerator used is net income before extra/preferred dividend (M_ACC_NET_PROFIT_ORDINARY), and the denominator is one-quarter lagged book equity, computed with quarterly data. Quarterly financial statement items are lagged by one quarter to ensure data is available to investors on the ranking date. All returns in the factor and portfolio constructions are total returns.

3.2 Value Portfolios

The construction of value portfolios is the double-sorted 2×3 value-weighted portfolios based on size and value dimension. The size dimension is big (B) and small (S) from the market capitalization of each stock. We split the value measures into high (H), medium (M), and low (L) portfolios, with the 70th and 30th percentiles as thresholds. The value portfolios take equally weighted long positions in HB and HS portfolios and equally weighted short positions in LB and LS portfolios, similar to the construction of Fama-French factors. Compared to single-sorted (unconditional) portfolios, the double-sorted portfolios can be viewed as conditional, size-neutral factors and deliver higher t-statistics in the Thai stock markets, as demonstrated by Charoenwong, Nettayanun, and Saengchote (2021). In this study, we analyze eight versions of the value premiums. The ratios representing value premiums are based on comparing accounting fundamentals of value in the balance sheet, income statement, and cash flow statement versus price. Each value portfolio captures how investors trade stock based on their belief of fundamental value, corresponding to the different accounting measures and market price.

Book-to-Market (BM)

The book-to-market (BM) ratio is prevalent in asset pricing research and investment management. The measure appears in the book *Security Analysis*, first published in 1934. Fama and French (1993) use this measure to construct the widely used Fama-French three-factor model. The HML factor is defined as high minus low BM. They find that stocks with high BM outperform stocks with low BM. The advantage of BM compared to other definitions (such as earnings-to-price ratio) is the stability of book equity compared to other flow-based measures, such as dividends or earnings. The t-statistics associated with this definition also tend to be higher, as evident in Linnainmaa and Roberts (2018) and Hou, Xue, and Zhang (2020). As described earlier, BM is computed from market capitalization as of December and the corresponding book equity.

Enterprise Book-to-Price (EBP)

Penman, Richardson, and Tuna (2007) argue that BM can decompose into two parts. First, the enterprise book-to-price (EBP) reflects the business's operational risk. The second part is the leverage component, which reflects the financing risk. They find that EBP has a positive relationship with stock returns. However, Hou, Xue, and Zhang (2020) find that BM has higher t-statistics than EBP. We define EBP as the sum of total debt (M_INT_BEARING_DEBT) and the book value of equity divided by the sum of total debt and market capitalization at December t-1.

Sales-to-Price (SP)

Revenue is another accounting measure that can capture value. Barbee, Mukherji, and Raines (1996) use the sale-to-price ratio (SP) and compare it to BM. They found that SP could explain stock returns from 1979 to 1991 while BM could not during the same period. They assert that SP has an advantage over BM because BM can sometimes be negative. They also argue that the measure SP is better than EP because sales are more stable than earnings. Linnainmaa and Roberts (2018) find that the SP premium was statistically insignificant during 1979-1991. Other than during that period, the premium is statistically significant. We define SP by sales (M_ACC_SALE) divided by market capitalization at December t-1 as SP.

Cash Flow-to-Price (CFP)

Lakonishok, Shleifer, and Vishny (1994) explore the cash flow-to-price (CFP) ratio as an alternative definition of value measure to show that behavioral biases can drive value premiums. They show that high CFP portfolios outperform low CFP portfolios over the one-year to five-year horizons. They argue that, while BM is about assets in place, CFP is more about the company's growth prospects. So, a low CFP indicates that investors might observe lower growth in the past and assume it will continue on the same trajectory. Thus, the motivation behind CFP already has a behavioral undertone to it. This study uses CFP using the net income (M_ACC_NET_PROFIT) plus depreciation and amortization (M_ACC_DP) divided by market capitalization at December t-1.

Operating Cash Flow-to-Price (OCP)

Recognizing the limitations of CFP, Desai, Rajgopal, and Venkatachalam (2004) adjust the regular CFP by using earnings and adding depreciation and working capital accruals divided by price. They use the new measure to explain the value and accruals anomalies from Sloan (1996) and argue that CFP lacks working capital accruals. Therefore, operating cash flow-to-price (OCP) should be a more refined measure of operating cash flow. Consequently, OCP can be a measure that captures both value and accrual premiums at the same time. In our study, the intention behind including OCP is to make it an improved version of CFP, as stated by Lakonishok, Shleifer, and Vishny (1994). We use net cash flow from operating activities (M_NET_OPERATING) divided by market capitalization at December t-1 as OCP.

Earnings-to-Price (EP)

Basu (1977, 1983) shows the relationship between stock returns and the earnings-to-price (EP) ratio, where portfolios with high EP tend to outperform portfolios with low EP. When screening for value stocks, EP is also a value measure that investors use. The ratio also appears in the *Security Analysis* book alongside BM and DP. Because earnings (when properly measured) represent the firm's profitability, some investors might prefer to focus more on this quantity than cash flow. As EP is a flow-based measure while BM is a stock-based measure, empirical evidence for EP and BM can differ. For example, Hou, Xue, and Zhang (2020) find that EP underperforms BM. Fama and French (1993) also favor BM over EP in constructing the HML factor. EP is net income (M_ACC_NET_PROFIT) divided by market capitalization at December t-1.

Dividend-to-Price (DP)

Another important measure is the dividend-to-price (DP) ratio. Litzenberger and Ramaswamy (1979) find a positive relationship between DP and stock returns. DP serves many roles in asset pricing theory. For example, in the Consumption-Based Capital Asset Pricing Model (CCAPM) (Cochrane, 2005), DP or dividend yield is a key input in the theoretical model and directly relates to returns predictability. Thus, it could be viewed as a fundamental input to a valuation exercise rather than a value premium. We define the DP ratio as cash dividend paid (M_DIVIDEND) divided by market capitalization at December t-1. Firms that have not paid dividends in the most recent year are excluded.

Enterprise Multiple (EM)

The original intention of Loughran and Wellman (2011) was to use enterprise multiple (EM) to capture discount rates: based on present value calculation, low (high) EM stocks have higher (lower) discount rates and thus should have higher (lower) returns. EM in Loughran and Wellman (2011) is the enterprise value divided by EBITDA. We invert the ratio so that the measure of value is consistent with other measures, where price (market value) is the denominator. We define EM as operating income before depreciation and amortization (M_ACC_EBIT) divided by the sum of market capitalization, preferred stock (M_PREFERRED_SHARES), total debt (M_INT_BEARING_DEBT) less cash (M_CASH). Therefore, high (low) EM means value (growth) stock.

3.3 Behavioral Factors

The two behavioral factors of Daniel, Hirshleifer, and Sun (2020) are the PEAD (post-earnings-announcement drift) factor, which is motivated by the observation that stock prices tend to “drift” upward (downward) after good (bad) earnings announcement, and the FIN (financing) factor, which is motivated by the observation that firms tend to issue (repurchase) equity when their stock prices are overpriced (underpriced). Both factors represent mispricing caused by inattentions and underreactions at short and long horizons. The factors are defined as follows:

PEAD

The post-earnings-announcement drift (PEAD) factor reflects investors' underreaction to earnings surprises, which results in stocks continuing to drift in the direction of an earnings surprise after the announcement. PEAD has been extensively documented, with Bernard and Thomas (1989) showing that investors often fail to immediately incorporate earnings surprises into stock prices, leading to predictable future returns. Fink (2021) shows that PEAD is a global phenomenon.

The factor takes a long position in stocks with positive earnings surprises and a short position in negative ones. Following Hirshleifer and Teoh (2003), we construct the PEAD factor-mimicking portfolio by ranking stocks based on their cumulative abnormal returns (CAR) versus the market two days before and one day after the date of quarterly earnings announcement obtained from the SETSMART database. The CAR for each stock is ranked at the end of each month, ensuring that the four-day window ends in the same month. The construction of the PEAD factor is the double-sorted 2×3 value-weighted portfolios based on size and mispricing and take a long position in stocks with the highest CARs. Unlike the value portfolios, the thresholds for high and low are the 80^{th} and 20^{th} percentiles.

FIN

Empirical evidence from Loughran and Ritter (1995) shows that firms that issue equity underperform in the long term due to over-optimism from investors and poor timing from managers. Daniel, Hirshleifer, and Sun (2020) construct the FIN factor by averaging the spreads from two methods of detecting net equity financing: first, one-year net share issuance (NSI) (Pontiff and Woodgate, 2008), and second, five-year composite share issuance (CSI) (Daniel and Titman, 2006), which is computed as the firm's five-year growth in market equity minus five-year total equity return. With CSI, any activity that results in equity, such as seasoned equity offering, stock-based compensation, or equity-financed acquisition, will increase the measure, while activities such as share repurchases and cash dividends will decrease the measure. Consequently, the financing measures of Daniel and Titman (2006) are more inclusive than those of Pontiff and Woodgate (2008). In addition, because share issuances and repurchases are relatively infrequent in Thailand, constructing a one-year NSI is problematic, so we opt to use only the five-year CSI of Daniel and Titman (2006). Because the PEAD factor is constructed with monthly rebalancing, we also construct the FIN factor with the same rebalancing frequency. We compute the rolling five-year CSI from each firm's total return index (TRI) and market capitalization monthly. The construction of the FIN factor is also the double-sorted 2×3 value-weighted portfolios and takes a long position in stocks with the lowest CSI (potentially negative). The thresholds for high and low are the 80th and 20th percentiles. We report our findings in the next section.

4. Results

4.1 Value Premiums

First, we demonstrate the existence of eight versions of the value premiums in Thailand. Table 1 Panel A reports the summary statistics for the long-short value portfolios. Six of the eight value premiums are statistically significant at the 5% level, and five have t-statistics greater than 3.0 — a more stringent threshold advocated by Harvey, Liu, and Zhu (2016). Two strategies are insignificant: EP and EM have very low long-short spreads and t-statistics of 1.64 and 1.50, respectively. The spread is the highest for the OCP portfolio at 0.653% per month, followed by the CFP portfolio at 0.591% per month. Like Arnott et al. (2021), the SP portfolio has a higher spread, t-statistic, and annualized Sharpe ratio than the BM portfolio (the ratio used for the Fama-French HML value factor). Some versions of the value premiums are more correlated, as illustrated by Panel B. For example, the correlation between the stock-type value premiums BM and EBP is 0.852. For the flow-type value premiums, the EM premium (formed based on EBITDA and EV) is highly correlated to premiums based on cash flow (CFP, OCP) and profits (EP).

Panel C reports the summary statistics for the long-short factors from the Fama-French six-factor and q-factor models. Similar to Charoenwong, Nettayanun, and Saengchote (2021), the size factors (SMB and ME) are insignificant, and the q-factor version of the profitability factor (ROE) has the highest monthly spread (1.180%) and is statistically highly significant, while the Fama-French version (RMW) has the lowest spread (0.147%) and is statistically insignificant.

Table 1: Value Premiums Summary Statistics.

This table reports the summary statistics for eight versions of value premium from July 2001 to September 2024. Panel A reports the monthly returns' mean, standard deviation, t-statistic, and annualized Sharpe ratio. Panel B reports the Pearson's correlation coefficients between each pair of value premiums. BM is the same as the Fama-French HML value factor in this definition. Panel C reports the descriptive statistics of factors from the Fama-French and the q-factor models.

Panel A: Descriptive statistics

	BM	EBP	SP	CFP	OCP	EP	DP	EM
Av M Ret	0.567	0.620	0.590	0.591	0.653	0.310	0.475	0.302
M Std Dev	3.10	3.30	3.01	3.29	3.01	3.17	2.78	3.37
t-Statistic	3.05	3.14	3.27	3.00	3.62	1.64	2.85	1.50
Ann SR	0.63	0.65	0.68	0.62	0.75	0.34	0.59	0.31

Panel B: Correlation matrix of value portfolios

	BM	EBP	SP	CFP	OCP	EP	DP	EM
BM	1.000							
EBP	0.852	1.000						
SP	0.415	0.448	1.000					
CFP	0.387	0.456	0.530	1.000				
OCP	0.234	0.253	0.423	0.526	1.000			
EP	0.159	0.226	0.207	0.735	0.364	1.000		
DP	-0.058	0.062	0.093	0.299	0.319	0.357	1.000	
EM	0.057	0.171	0.220	0.580	0.406	0.678	0.479	1.000

Panel C: Descriptive statistics of factors from Fama-French and q-factor models

	MKT	SMB	HML	RMW	CMA	UMD	ME	I/A	ROE
Av M Ret	0.859	0.213	0.567	0.147	0.416	0.954	0.419	0.437	1.180
M Std Dev	5.70	3.81	3.10	2.94	3.04	4.66	3.62	2.96	3.60
t-Statistic	2.52	0.93	3.05	0.84	2.28	3.42	1.94	2.47	5.48
Ann SR	0.52	0.19	0.63	0.17	0.47	0.71	0.40	0.51	1.14

Table 2: Value Premium Alphas.

This table reports the time-series regression of the eight value premium portfolios on (1) the CAPM, (2) the Fama-French model excluding the HML factor, and (3) the q-factor model. Only the alphas, the t-statistic, and the adjusted R-squared are reported for brevity. The Newey-West (1987) adjusted t-statistics are reported in square brackets. Stars correspond to the statistical significance level, with *, **, and *** representing 10%, 5%, and 1%, respectively.

$$v_t = \alpha + \sum_j \beta_j f_{j,t} + \varepsilon_t$$

	(1) BM	(2) EBP	(3) SP	(4) CFP	(5) OCP	(6) EP	(7) DP	(8) EM
CAPM	0.433**	0.509***	0.494***	0.531***	0.698***	0.341*	0.546***	0.393*
t-Statistic	[2.34]	[2.62]	[2.73]	[2.72]	[4.10]	[1.78]	[3.42]	[1.92]
Adj R-Sq	0.079	0.047	0.042	0.011	0.006	0.001	0.025	0.029
Fama-French	0.472**	0.534**	0.311*	0.342*	0.437***	0.367**	0.530***	0.331**
t-Statistic	[2.36]	[2.51]	[1.85]	[1.91]	[2.88]	[2.18]	[3.42]	[2.01]
Adj R-Sq	0.178	0.073	0.070	0.171	0.237	0.242	0.240	0.480
q-Factor	0.617***	0.675***	0.300*	0.333*	0.473***	0.232	0.458***	0.410**
t-Statistic	[3.31]	[3.26]	[1.68]	[1.84]	[2.89]	[1.25]	[2.69]	[2.10]
Adj R-Sq	0.180	0.095	0.074	0.116	0.153	0.142	0.203	0.218

Finally, we assess the value portfolios against asset pricing models. Because the Fama-French model already contains the value factor, we omit HML. We use the time-series regression models from Equation 1.

$$v_t = \alpha + \sum_j \beta_j f_{j,t} + \varepsilon_t \tag{1}$$

Let v_t be the time series of a value portfolio, f_{jt} the times series of factor j from an asset pricing model. If the factor contributes to the pricing of the value portfolio, then α should be insignificant, β_k should be statistically different from zero. The alphas are reported in Table 2, and the factor loadings are reported in Appendix 1 for brevity. The value portfolios' alphas are all statistically significant against the CAPM and mostly against the Fama-French and the q-factor models, suggesting that the value premium exists in Thailand and cannot be explained by popular asset pricing models. Notably, the q-factor model does not explain the "classic" Fama-French value premium formed on the book-to-market ratio.

4.2 Behavioral Factors

Having established the presence of the value premium in Thailand, we create the Daniel, Hirshleifer, and Sun (2020) PEAD and FIN behavioral factors. The summary statistics of the factors are presented in Table 3, and the correlations to other factors are reported in Appendix 2. Both factors are statistically significant, with monthly spreads of 1.508% for PEAD and 0.636% for FIN. Notably, the spread and the t-statistic of PEAD is 1.508% per month and 7.98 – the highest of all factors, including the Fama-French and q-factors – and its annualized Sharpe ratio is extremely high at 1.65, making it an attractive investing strategy on its own.

Table 3: Behavioral Factors.

This table reports the descriptive statistics of the behavioral factors from the Daniel, Hirshleifer, and Sun (2020) model. The PEAD (post-earnings-announcement drift) factor-mimicking portfolio is constructed by ranking stocks based on their cumulative abnormal returns (CAR) versus the market two days before and one day after the date of the quarterly earnings announcement obtained from the SETSMART database. The FIN factor is constructed from Daniel and Titman's (2006) five-year composite share issuance (CSI), computed as the firm's five-year growth in market equity minus five-year total equity return.

	PEAD	FIN
Average Monthly Return	1.508	0.636
Monthly Standard Deviation	3.16	4.55
t-Statistic	7.98	2.34
Annualized Shape Ratio	1.65	0.48

Figure 1: Behavioral Factors Cumulative Wealth Index

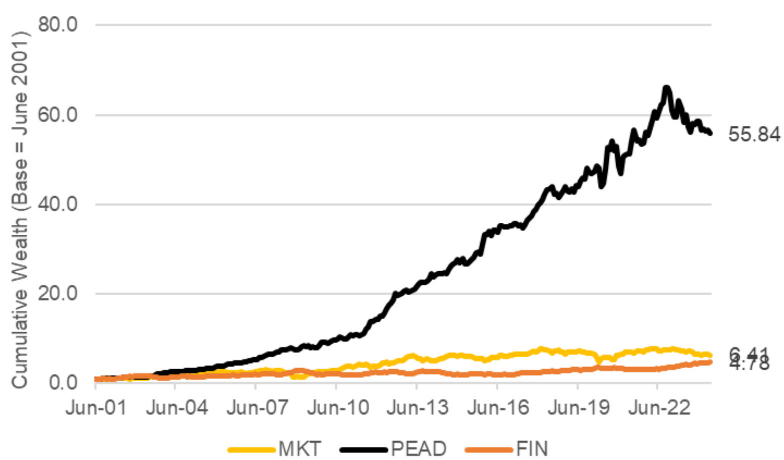
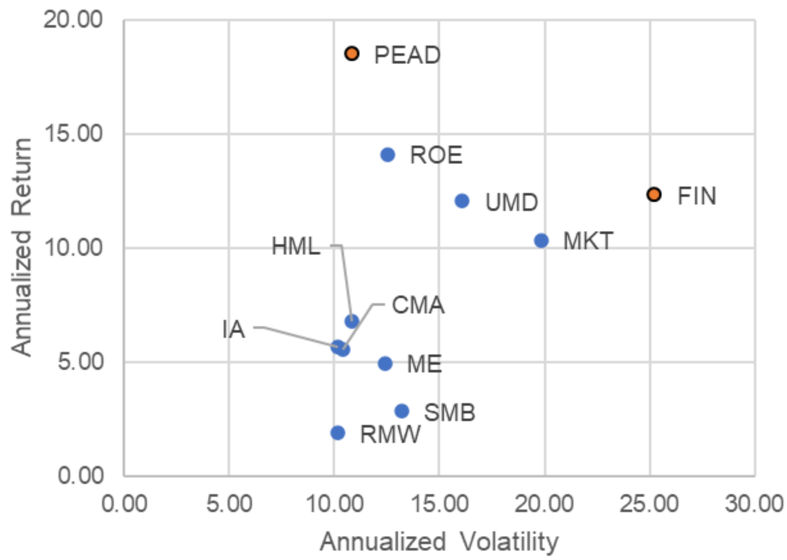


Figure 2: Behavioral Factors Versus Fama-French Factors and q-Factors



We use the factor-spanning test to establish the behavioral factors' validity further. The idea is that relevant factors in an asset pricing model should not be spannable – that is, the factor should not be a linear combination of the existing factors of an asset pricing model. We follow the same approach as Equation 1, except we use PEAD and FIN as dependent variables. We report the results in Table 4. Panel A shows the regressions of the behavioral factors onto the Fama-French and the q-factors. The first (third) column is the time-series regression for PEAD on the Fama-French six-factor (q-factor) model. The second (fourth) column is the time-series regression for FIN on the Fama-French six-factor (q-factor) model.

Under both the Fama-French six-factor model (with HML) and the q-factor model, PEAD and FIN are not spannable, and the alphas are statistically significant at the 1% level. HML and UMD factors can partially explain PEAD. In addition, the MKT (negative), SMB (negative), HML (weakly positive), and RMW (positive) from the Fama-French model can partially explain FIN. For the q-factor, MKT (negative), ME (negative), and ROE (positive) can also partially explain FIN. Since FIN reflects repurchases and issuances, the loadings suggest that large and profitable firms are more likely to engage in share repurchases. In summary, PEAD and FIN are not spanned by the Fama-French or q-factor models and have very high spreads.

We also examine whether the behavioral factors can span the Fama-French and q-factors. As discussed earlier, RMW is not statistically significant in our sample, so it is not surprising that its alpha is statistically insignificant. However, the 3-factor behavioral model spans HML, suggesting that the value premium (at least one form) may result from behavioral biases and market mispricing. The results are also quite different from the US results in Daniel, Hirshleifer, and Sun (2020), where the 3-factor model also explains UMD and ROE, while UMD and ROE remain statistically significant in our sample. While the factor loading of PEAD is positive at 0.297 and statistically significant at 1% for explaining UMD, the PEAD loading in the US sample is 1.11, suggesting that momentum in Thailand is only partly driven by post-earnings-announcement drift (which is a type of momentum). The prevalence value and momentum are consistent with Asness, Moskowitz, and Pedersen (2013).

Our analyses demonstrate the validity of the behavioral factors. Next, we use the 3-factor behavioral model to assess the value premiums.

Table 4: Spanning Regressions of Behavioral Factors.

Panel A shows the results of factor-spanning regressions of the Daniel, Hirshleifer, and Sun (2020) behavioral factor model on the Fama-French six-factor and q-factor models. Panel B shows the results of factor-spanning regressions of the Fama-French six-factor and the q-factor models on the behavioral factor models. Returns are represented in percentage points. The absolute values of the Newey-West (1987) adjusted t-statistics are reported in square brackets. Stars correspond to the statistical significance level, with *, **, and *** representing 10%, 5%, and 1%, respectively.

Panel A: Do the Fama-French and q-factors explain the behavioral factors?

	(1) PEAD	(2) FIN	(3) PEAD	(4) FIN
MKT	-0.024	-0.470***	-0.014	-0.492***
	[-0.49]	[-10.22]	[-0.29]	[-10.48]
SMB	0.041	-0.224***		
	[0.46]	[-3.64]		
HML	0.141**	0.155**		
	[2.08]	[2.00]		
RMW	0.062	0.551***		
	[0.82]	[6.37]		
CMA	-0.062	0.214***		
	[-0.66]	[2.71]		
UMD	0.148***	-0.002		
	[2.69]	[-0.03]		
ME			0.081	-0.246***
			[0.88]	[-3.69]
I/A			-0.072	-0.092
			[-0.85]	[-1.12]
ROE			0.087	0.346***
			[1.43]	[6.04]
Alpha	1.316***	0.832***	1.415***	0.794***
	[6.90]	[4.59]	[7.42]	[3.72]
Adj. R-Sq.	0.044	0.511	0.009	0.458

Panel B: Do the behavioral factors explain the Fama-French and q-factors?

	(1) SMB	(2) HML	(3) RMW	(4) CMA	(5) UMD	(6) ME	(7) I/A	(8) ROE
MKT	-0.331***	0.164***	0.057	-0.095*	-0.137	-0.270***	-0.075	0.051
	[-4.84]	[3.17]	[1.15]	[-1.96]	[-1.63]	[-4.50]	[-1.63]	[0.65]
PEAD	0.075	0.094	0.017	-0.001	0.297***	0.108	-0.046	0.089
	[0.74]	[1.58]	[0.29]	[-0.01]	[2.67]	[1.06]	[-0.60]	[1.18]
FIN	-0.329***	0.010	0.309***	0.023	0.022	-0.224***	-0.007	0.312***
	[-4.09]	[0.20]	[4.43]	[0.38]	[0.24]	[-2.79]	[-0.13]	[5.17]
Alpha	0.594**	0.278	-0.123	0.483**	0.611*	0.632***	0.575**	0.804***
	[2.56]	[1.29]	[-0.72]	[2.17]	[1.88]	[2.67]	[2.56]	[3.52]
Adj. R-Sq.	0.161	0.081	0.170	0.030	0.068	0.118	0.010	0.123

4.3 Pricing Value Premium with Behavioral Factors

In this section, we price the eight value premium portfolios with the Daniel, Hirshleifer, and Sun (2020) 3-factor behavioral model, MKT, PEAD, and FIN using Equation 2.

$$v_t = \alpha + \beta_{MKT}MKT_t + \beta_{PEAD}PEAD_t + \beta_{FIN}FIN_t + \varepsilon_t \tag{2}$$

Let v_t be the time series of a value portfolio, MKT_t be the times series of the market risk premium (market return minus the risk-free rate), $PEAD_t$ be the PEAD factor, FIN_t be the FIN factor. The results are reported in Table 5. We already saw in Table 4 Panel B that the 3-factor model explains BM. The alphas of CFP, EP, and EM are insignificant, while the significance of EBP is reduced. Based on adjusted R-squared values, the behavioral model can explain more variations than the CAPM but less than the Fama-French model without HML and the q-factor model. However, the behavioral factor model outperforms all three models in Table 2 based on the alphas. Given that most analysts use the BM, CFP, and EP ratios to form value strategies, we conclude that the behavioral factors (PEAD and FIN) can explain the value premiums.

The results in Table 4 Panel B also show that the pure behavioral model cannot fully explain all Fama-French factors and q-factors. In the next section, we explore whether augmenting the "classical" Fama-French and q-factor models with PEAD and FIN can better explain the value premium portfolios.

Table 5: Value factors and behavioral factors.

This table reports the time-series regression of the eight value premium portfolios on the 3-factor behavioral model. The PEAD (post-earnings-announcement drift) factor-mimicking portfolio is constructed by ranking stocks based on their cumulative abnormal returns (CAR) versus the market two days before and one day after the date of the quarterly earnings announcement obtained from the SETSMART database. The FIN factor is constructed from Daniel and Titman's (2006) five-year composite share issuance (CSI), computed as the firm's five-year growth in market equity minus five-year total equity return. The Newey-West (1987) adjusted t-statistics are reported in square brackets. Stars correspond to the statistical significance level, with *, **, and *** representing 10%, 5%, and 1%, respectively.

$$v_t = \alpha + \beta_{MKT} MKT_t + \beta_{PEAD} PEAD_t + \beta_{FIN} FIN_t + \varepsilon_t$$

	(1) BM	(2) EBP	(3) SP	(4) CFP	(5) OCP	(6) EP	(7) DP	(8) EM
MKT	0.164***	0.143***	0.113**	0.203***	0.092	0.125**	0.052	0.091
	[3.17]	[2.60]	[2.15]	[3.16]	[1.30]	[2.02]	[0.81]	[1.46]
PEAD	0.094	0.065	0.003	0.121	0.041	0.128*	-0.071	0.089
	[1.58]	[1.06]	[0.04]	[1.55]	[0.56]	[1.70]	[-1.13]	[1.24]
FIN	0.010	0.024	0.002	0.271***	0.299***	0.327***	0.285***	0.404***
	[0.20]	[0.44]	[0.03]	[3.87]	[4.40]	[4.10]	[4.45]	[4.97]
Alpha	0.278	0.383*	0.487***	0.062	0.321**	-0.199	0.356**	-0.168
	[1.29]	[1.75]	[2.70]	[0.33]	[2.02]	[-1.10]	[2.30]	[-0.94]
Adj. R-Sq.	0.081	0.044	0.035	0.110	0.133	0.155	0.163	0.224

4.4 Augmented Models with Behavioral Factors

Finally, we augment the asset pricing models with the behavioral factors and price the eight value premium portfolios. We regress the value portfolios on the augmented factor models following Equation 3.

$$v_t = \alpha + \sum_j \beta_j f_{jt} + \beta_{PEAD} PEAD_t + \beta_{FIN} FIN_t + \varepsilon_t \tag{3}$$

Let v_t be the time series of a value portfolio, f_{jt} the times series of factor j from an asset pricing model, $PEAD_t$ be the PEAD factor, and FIN_t be the FIN factor. If the behavioral factor contributes to the pricing of the value portfolio, then α should decrease from the original Fama-French/q-factor model, β_{PEAD} or β_{FIN} should be statistically different from zero, and the adjusted R-squared values should also increase. The augmented Fama-French model is reported in Table 6, Panel A, and the augmented q-factor model in Panel B. Compared to the baseline results in Table

2, the augmented models perform better as there are fewer remaining unpriced portfolios than the traditional models, and the adjusted R-squared values are higher for almost all the models. Specifically, the significant alphas (at 5% level) reduce from six (BM, EBP, OCP, EP, DP, EM) to two (SP, DP) for the Fama-French model and from 5 (BM, EBP, OCP, DP, EM) to 2 (EBP, DP) for the q-factor model. DP remains statistically significant in both models, with monthly alphas of 0.485% for the Fama-French model and 0.409% for the q-factor model. Both are also statistically significant at the 5% level.

Dividend yield plays many important roles in finance. While dividend yield is a key component in asset pricing and has been included as a version of the value premium, many influential corporate finance theories seek to explain why firms pay dividends. For example, Ross (1977) and Bhattacharya (1979) argue that firms pay dividends to signal their quality in information asymmetry. They may also pay dividends to reduce the agency cost of free cash flow, as presented by Jensen (1986). Denis and Osobov (2008), who studied firms in six countries between 1998 and 2002, cast doubt on the various dividend theories, including the signaling theory for firms outside the US. They conclude that the agency cost-based theory can better explain dividend behavior, consistent with the findings in Thailand by Fairchild, Guney, and Thanatawee (2014).

Firms that pay dividends may be motivated by factors beyond those traditionally captured by asset pricing models. The persistent significance of DP in both the Fama-French and q-factor models shows that dividend yield remains a key driver of returns. Our evidence suggests that behavioral and corporate governance considerations could influence asset prices in ways not fully explained by classical finance theories.

Table 6: Augmented Fama-French and q-factor models.

This table reports the time-series regression of the eight value premium portfolios on the augmented Fama-French (Panel A) and q-factor models (Panel B). The PEAD (post-earnings-announcement drift) factor-mimicking portfolio is constructed by ranking stocks based on their cumulative abnormal returns (CAR) versus the market two days before and one day after the date of the quarterly earnings announcement obtained from the SETSMART database. The FIN factor is constructed from Daniel and Titman's (2006) five-year composite share issuance (CSI), computed as the firm's five-year growth in market equity minus five-year total equity return. The Newey-West (1987) adjusted t-statistics are reported in square brackets. Stars correspond to the statistical significance level, with *, **, and *** representing 10%, 5%, and 1%, respectively.

$$v_t = \alpha + \sum\nolimits_k \beta_k f_{kt} + \beta_{PEAD} PEAD_t + \beta_{FIN} FIN_t + \varepsilon_t$$

Panel A: Augmented Fama-French model

	(1) BM	(2) EBP	(3) SP	(4) CFP	(5) OCP	(6) EP	(7) DP	(8) EM
MKT	0.185***	0.160***	0.132***	0.161***	0.070	0.031	-0.021	-0.018
	[3.81]	[2.94]	[2.87]	[2.95]	[1.57]	[0.63]	[-0.40]	[-0.45]
SMB	-0.012	0.003	0.004	-0.149**	-0.149*	-0.205***	-0.190***	-0.225***
	[-0.22]	[0.05]	[0.05]	[-2.30]	[-1.83]	[-3.80]	[-2.84]	[-5.30]
RMW	-0.359***	-0.257***	0.139	0.295***	0.226**	0.302***	0.217***	0.521***
	[-5.48]	[-2.89]	[1.46]	[3.03]	[2.22]	[3.13]	[2.96]	[6.93]
CMA	0.101	0.035	0.168**	0.240***	0.327***	-0.015	-0.016	-0.098
	[1.55]	[0.43]	[2.54]	[3.26]	[5.31]	[-0.22]	[-0.23]	[-1.63]
UMD	-0.035	-0.011	0.068	0.017	0.064	-0.055	0.030	0.034
	[-0.59]	[-0.17]	[1.17]	[0.35]	[1.56]	[-1.13]	[0.75]	[0.80]
PEAD	0.111*	0.073	-0.020	0.122*	0.030	0.155**	-0.070	0.087*
	[1.95]	[1.15]	[-0.28]	[1.67]	[0.49]	[2.29]	[-1.27]	[1.76]
FIN	0.116**	0.104	-0.046	0.124*	0.171***	0.168**	0.156***	0.171***
	[2.03]	[1.54]	[-0.73]	[1.81]	[3.77]	[2.36]	[2.60]	[2.65]
Alpha	0.213	0.339	0.379**	0.061	0.241	0.001	0.485***	0.056
	[1.00]	[1.51]	[2.15]	[0.32]	[1.55]	[0.01]	[3.04]	[0.32]
Adj. R-Sq.	0.200	0.081	0.066	0.194	0.267	0.291	0.271	0.510

Panel B: Augmented q-factor model

	(1) BM	(2) EBP	(3) SP	(4) CFP	(5) OCP	(6) EP	(7) DP	(8) EM
MKT	0.212***	0.177***	0.128***	0.169***	0.060	0.055	-0.019	-0.002
	[4.33]	[3.10]	[2.85]	[2.95]	[1.37]	[1.01]	[-0.38]	[-0.03]
ME	0.127**	0.093	0.002	0.138**	0.057	0.133**	-0.070	0.100
	[2.30]	[1.50]	[0.02]	[2.09]	[0.96]	[2.06]	[-1.33]	[1.59]
I/A	0.118**	0.109*	-0.016	0.206***	0.230***	0.233***	0.186***	0.309***
	[2.22]	[1.72]	[-0.26]	[3.11]	[4.51]	[3.15]	[3.37]	[3.86]
ROE	0.049	0.026	0.023	-0.160**	-0.153*	-0.203***	-0.202***	-0.268***
	[0.93]	[0.37]	[0.29]	[-2.18]	[-1.71]	[-3.24]	[-3.14]	[-4.36]
PEAD	0.257***	0.189**	0.172***	0.193***	0.203***	-0.091	-0.109*	-0.193***
	[4.07]	[2.58]	[2.95]	[2.78]	[3.05]	[-1.34]	[-1.68]	[-2.70]
FIN	-0.303***	-0.247***	0.078	0.097	0.115	0.152**	0.171**	0.110*
	[-5.44]	[-2.98]	[0.84]	[1.19]	[1.02]	[2.34]	[2.18]	[1.81]
Alpha	0.343*	0.457**	0.311*	-0.027	0.209	-0.140	0.409**	0.024
	[1.71]	[2.16]	[1.73]	[-0.14]	[1.25]	[-0.69]	[2.43]	[0.13]
Adj. R-Sq.	0.208	0.109	0.067	0.172	0.217	0.215	0.253	0.316

5. Conclusions

Our research provides robust evidence that value investment strategies yield statistically significant premiums in the Thai stock market, reinforcing the effectiveness of value investing approaches based on accounting fundamentals. This finding supports the principle of a “margin of safety” central to value investing—stocks with stronger fundamentals relative to their prices tend to outperform.

While traditional models like the Fama-French and q-factor models capture much of this variability, the persistence of value premiums, particularly for the dividend-to-price (DP) portfolio, suggests that additional factors, including behavioral biases and governance considerations, are at play. The ongoing debate between risk-based and behavioral explanations for value premiums, as highlighted by Asness et al. (2015), reflects this complexity.

Our results show that augmenting these models with behavioral factors such as post-earnings-announcement drift (PEAD) and net equity issuance (FIN) significantly improves their ability to explain value premiums. However, the DP portfolio remains an anomaly. As dividend policy in Thailand can be related to agency cost (Fairchild, Guney, and Thanatawee, 2014), this variant of value strategy may reflect the presence of information asymmetry in the market.

Ultimately, our research highlights the importance of expanding traditional asset pricing models to account for behavioral biases (and perhaps corporate governance). Doing so gives us a more comprehensive understanding of stock returns, especially in emerging markets like Thailand, where inefficiencies and governance issues can be more pronounced. These insights contribute to academic discussions and offer practical implications for investors employing value investing strategies.

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Appendix 1: Value Premium and Asset Pricing Models.

This table reports the time-series regression of the eight value premium portfolios. The table reports the factor loading(s), the alphas, t-statistics, and adjusted R-squared. Panel A uses the CAPM model. Panel B uses the Fama-French model, excluding the HML factor. Panel C uses the q-factor model. The absolute values of the Newey-West (1987) adjusted t-statistics are reported in square brackets. Stars correspond to the statistical significance level, with *, **, and *** representing 10%, 5%, and 1%, respectively.

Panel A: CAPM

	(1) BM	(2) EBP	(3) SP	(4) CFP	(5) OCP	(6) EP	(7) DP	(8) EM
MKT	0.156***	0.129***	0.112***	0.069	-0.053	-0.036	-0.083	-0.106*
	[3.65]	[2.72]	[2.69]	[1.39]	[-0.97]	[-0.73]	[-1.50]	[-1.80]
Alpha	0.433**	0.509***	0.494***	0.531***	0.698***	0.341*	0.546***	0.393*
	[2.34]	[2.62]	[2.73]	[2.72]	[4.10]	[1.78]	[3.42]	[1.92]
Adj. R-Squared	0.079	0.047	0.042	0.011	0.006	0.001	0.025	0.029

Panel B: Fama-French (excluding HML)

	(1) BM	(2) EBP	(3) SP	(4) CFP	(5) OCP	(6) EP	(7) DP	(8) EM
MKT	0.132***	0.113**	0.152***	0.105**	-0.007	-0.045	-0.090**	-0.095***
	[3.13]	[2.19]	[3.24]	[2.31]	[-0.15]	[-1.17]	[-1.99]	[-2.79]
SMB	-0.035	-0.018	0.013	-0.174***	-0.187**	-0.237***	-0.228***	-0.261***
	[-0.65]	[-0.29]	[0.18]	[-2.87]	[-2.31]	[-4.44]	[-3.59]	[-6.50]
RMW	-0.298***	-0.203**	0.116	0.361***	0.313***	0.390***	0.294***	0.609***
	[-4.75]	[-2.39]	[1.35]	[4.22]	[3.16]	[4.48]	[4.45]	[9.65]
CMA	0.123*	0.056	0.158**	0.264***	0.365***	0.017	0.023	-0.062
	[1.86]	[0.72]	[2.50]	[3.55]	[5.83]	[0.24]	[0.32]	[-1.00]
UMD	-0.020	-0.001	0.066	0.034	0.067	-0.034	0.020	0.046
	[-0.35]	[-0.01]	[1.17]	[0.74]	[1.51]	[-0.71]	[0.51]	[1.11]
Alpha	0.472**	0.534**	0.311*	0.342*	0.437***	0.367**	0.530***	0.331**
	[2.36]	[2.51]	[1.85]	[1.91]	[2.88]	[2.18]	[3.42]	[2.01]
Adj. R-Squared	0.178	0.073	0.070	0.171	0.237	0.242	0.240	0.480

`Panel C: Hou, Xue, and Zhang (2015) q-factor model

	(1) BM	(2) EBP	(3) SP	(4) CFP	(5) OCP	(6) EP	(7) DP	(8) EM
MKT	0.152***	0.122**	0.136***	0.066	-0.054	-0.061	-0.110**	-0.155***
	[3.78]	[2.41]	[3.17]	[1.45]	[-1.27]	[-1.48]	[-2.42]	[-3.45]
ME	0.031	0.007	0.027	-0.199***	-0.205**	-0.250***	-0.253***	-0.336***
	[0.62]	[0.11]	[0.35]	[-2.81]	[-2.30]	[-3.82]	[-3.98]	[-5.62]
I/A	0.237***	0.172**	0.174***	0.164**	0.177***	-0.121*	-0.121*	-0.229***
	[3.58]	[2.23]	[2.94]	[2.22]	[2.66]	[-1.65]	[-1.70]	[-2.78]
ROE	-0.251***	-0.201***	0.072	0.181**	0.199*	0.244***	0.230***	0.225***
	[-5.22]	[-2.77]	[0.85]	[2.24]	[1.86]	[3.74]	[3.07]	[3.73]
Alpha	0.617***	0.675***	0.300*	0.333*	0.473***	0.232	0.458***	0.410**
	[3.31]	[3.26]	[1.68]	[1.84]	[2.89]	[1.25]	[2.69]	[2.10]
Adj. R-Squared	0.180	0.095	0.074	0.116	0.153	0.142	0.203	0.218

Appendix 2: Factor Correlation Matrix.

	MKT	SMB	HML	RMW	CMA	UMD	ME	I/A	ROE	PEAD	FIN
MKT	1.000										
SMB	-0.263	1.000									
HML	0.286	-0.044	1.000								
RMW	-0.179	-0.193	-0.358	1.000							
CMA	-0.198	0.106	0.152	-0.321	1.000						
UMD	-0.192	0.143	-0.068	0.056	0.251	1.000					
ME	-0.262	0.938	-0.048	-0.126	0.060	0.157	1.000				
I/A	-0.134	0.049	0.132	-0.258	0.850	0.242	0.024	1.000			
ROE	-0.161	-0.116	-0.290	0.406	0.122	0.457	0.053	0.198	1.000		
PEAD	-0.057	0.068	0.080	0.038	0.011	0.212	0.103	-0.042	0.095	1.000	
FIN	-0.601	-0.092	-0.160	0.414	0.141	0.133	-0.021	0.072	0.351	0.055	1.000