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A Technology Factor in the Indonesian Cross Section: Sector Return, Beta Compression and the Price of Technology Risk, 2010 to 2025

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Abstract

Theories of investment-specific technology shocks and displacement risk predict that returns in the technology-producing sector are a priced factor. This study builds that factor for the Indonesia Stock Exchange using 87,997 monthly returns from 894 companies between 2010 and 2025, a period in which the listed technology sector grew from six firms to thirty-six. The TECH factor earns 0.64 percent a month with a t-statistic of 0.81 and is spanned by the market, size, value, and momentum factors. Portfolios sorted on the technology beta earn high-minus-low spreads of minus 0.12 percent (equal-weighted) and 0.28 percent (value-weighted), and the second-pass price of technology risk ranges from minus 0.39 to 1.38 percent a month across four sets of test assets. The explanation lies in the exposures: a pre-ranking beta spread of 1.04 compresses to between 0.12 and 0.31 after formation, so the premium the factor earns would need 600 to 1,791 years of monthly data to detect. Exposure is concentrated in the sector itself, and the technology beta rises with Tobin's q and falls with book-to-market, as the theory predicts. The results provide a baseline for pricing digital economy risk as the sector broadens.

Keywords technology factor, investment specific shocks, beta compression, statistical power, cross section of returns, Indonesia.

1. Introduction

The idea that technological change is a source of priced risk has a long pedigree in asset pricing theory. Greenwood et al. (1997) showed that shocks to the technology for producing new capital goods account for a large share of postwar growth in the United States, and Papanikolaou (2011) placed those shocks in a two sector general equilibrium model. In that model the return of investment goods producers in excess of consumption goods producers carries a negative price of risk, because states in which new capital becomes cheap are states in which the marginal value of existing wealth is high. Kogan and Papanikolaou (2014) showed that firms with more growth opportunities load more heavily on that factor and earn lower returns. Gârleanu et al. (2012) reached a related conclusion through displacement risk. In each of these models the return of the technology producing sector carries the shock, and exposure to it should be compensated across every other firm.

Almost all of the evidence for this proposition comes from the United States, where the technology producing sector is large, old and diversified. Indonesia offers a contrasting and timely setting. The Indonesia Stock Exchange had six listed technology firms with a computable

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return in 2010, holding a fifth of a per cent of market capitalisation, and thirty six in 2025. In between, the exchange introduced a dedicated Technology sector in its 2021 classification, and the two largest initial public offerings in its history, both internet platforms, arrived in 2021 and 2022. The transformation of the national digital ecosystem therefore took place inside the sample, which makes the market a natural laboratory for asking when a technology sector becomes priced across the economy.

This study builds the factor and tests it with the standard tools of empirical asset pricing. The factor, TECH, is the return of the technology sector in excess of a size matched benchmark of the other sectors, with the sector leg weighted by lagged capitalisation and no firm allowed more than a quarter of it. The tests comprise rolling betas, beta sorted portfolios, Fama and MacBeth (1973) regressions, spanning regressions, the Gibbons et al. (1989) test and second pass regressions with the Shanken (1992) correction. The estimation sample for the beta sorts contains 51,973 firm months for 716 firms from January 2012 after a microcap screen.

The factor exists as a well defined return, and its exposures are what determine how it prices the cross section. TECH earns 0.64 per cent a month with a t statistic of 0.81, and its four factor alpha is 0.50 per cent with a t statistic of 0.69. Portfolios sorted on the technology beta earn a high minus low spread of minus 0.12 per cent a month equal weighted and 0.28 per cent value weighted. The pre ranking beta spread between extreme quintiles is 1.04, while the post ranking spread is 0.12 equal weighted and 0.31 value weighted. With exposures this compressed, a premium of the size the factor earns would need between 600 and 1,791 years of data to detect, which places the result in the power of the test.

Three further results describe where the exposure lives. The technology sector portfolio loads on TECH at 0.95, while 8.7 per cent of 699 non technology firms load at conventional significance and incumbent sectors load between minus 0.20 and 0.07. The technology beta rises with Tobin's q and falls with book to market, the direction that Kogan and Papanikolaou (2014) predict. When the identical procedure is applied to each of the other nine sectors, technology sits inside the range the other sectors produce on every diagnostic.

The study contributes in three ways. It tests the theory of technology risk in a market where the technology sector is being created, and shows that the growth opportunity channel is visible before the premium can be identified. It adds to the literature on factor discipline of Harvey et al. (2016), Hou et al. (2020) and Jensen et al. (2023) a worked example in which compression and power are measured before a premium is claimed or dismissed. It also provides benchmark numbers for pricing digital economy risk in Indonesia and comparable emerging markets.

2. Literature Review

The production side of asset pricing begins with Cochrane (1991), who showed that the investment return of a firm equals its stock return along the optimal path, and with Zhang (2005), who derived the value premium from costly reversibility. Greenwood et al. (1997) documented the steady fall in the relative price of equipment and attributed much of postwar productivity growth to investment specific technological change. Papanikolaou (2011) showed

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that when the technology for producing capital improves, the value of installed capital falls, so households that own installed capital are relatively worse off even as prospects improve. Assets whose payoffs rise with these shocks are therefore hedges, and the factor that proxies for the shock carries a negative price of risk. Kogan and Papanikolaou (2013, 2014) showed that firms rich in growth opportunities have higher exposures and lower expected returns, and Kung and Schmid (2015) and Lin (2012) linked innovation to the equity and value premia.

A second route to the same factor runs through the distribution of the gains from innovation. Gârleanu et al. (2012) model an economy in which new firms and new blueprints displace the wealth of incumbents who cannot fully share in them. Kogan et al. (2020) measure the redistribution with patent data and find that innovation transfers value from incumbents to innovators on a large scale. Corhay et al. (2020) show that entry and markups generate predictable variation in expected returns. The displacement view adds a sharp cross sectional prediction: incumbents in the industries that a new technology enters should load negatively on the innovation factor. In Indonesia the natural candidates are the consumer, infrastructure and transportation sectors with which platforms and payment technology compete.

Testing these predictions requires exposures that can be measured with precision. Blume (1975) and Vasicek (1973) showed that estimated betas regress toward one, and Dimson (1979) adjusted betas for thin trading. Fama and French (1992) assigned post ranking portfolio betas to reduce the errors in variables problem, and Levi and Welch (2017) found that the best forecast of a future beta shrinks the historical estimate heavily. Lewellen et al. (2010) showed that test assets with a strong factor structure make almost any factor look successful, and Harvey et al. (2016) and Hou et al. (2020) set demanding standards for new factors. Bessembinder et al. (2023) document how skewed individual stock returns are worldwide, which is the statistical reason cross sectional tests need long samples.

The standard factors are well documented in emerging markets. Cakici et al. (2013) find value and momentum in eighteen emerging markets including Indonesia, and Hanauer and Lauterbach (2019) find that value, momentum and profitability survive across emerging markets. Bekaert et al. (2007) show that liquidity is priced in emerging markets, Lesmond (2005) and Rhee and Wang (2009) document the role of thin trading and foreign ownership in emerging and Indonesian liquidity. Moskowitz and Grinblatt (1999) showed that industry returns carry momentum of their own, so a sector return can resemble a priced factor for reasons unrelated to technology.

Four hypotheses follow, and Figure 1 summarises the research model. H1 states that the technology factor earns a mean return that the market, size, value and momentum factors do not span. H2 states that firms with a higher technology beta earn lower subsequent returns, so that the beta carries a negative price in sorted portfolios and in individual stock regressions. H3 states that exposure to the technology factor is dispersed across the non technology sectors and is negative for incumbent sectors that the technology displaces. H4 states that exposure to the technology factor rises with growth opportunities, measured by Tobin's q, and falls with book to market.

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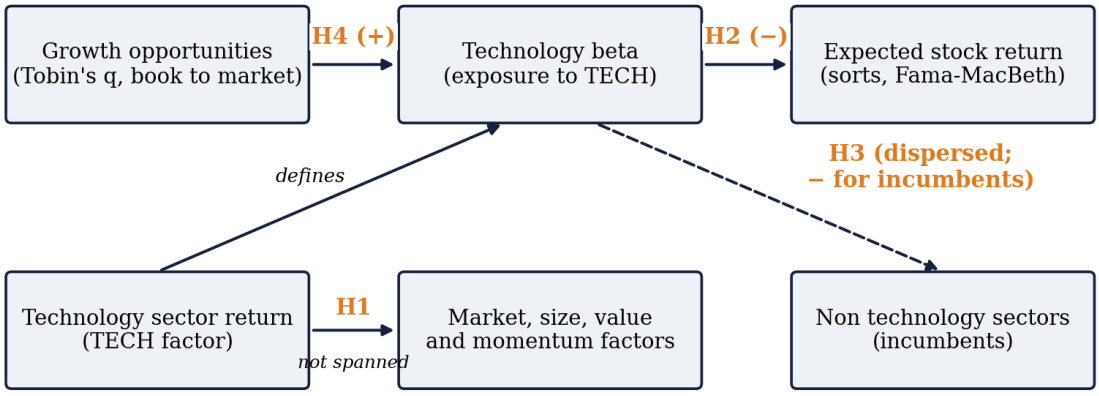


Figure 1. Research model. (Source: developed by the author from Papanikolaou (2011), Kogan and Papanikolaou (2014) and Gârleanu et al. (2012))

3. Research Method

The data are Bloomberg records of Indonesian listed equities held at the Bloomberg Laboratory of Universitas Diponegoro. Monthly returns are compounded from daily returns adjusted for splits, rights issues and bonus shares, and each return rests on at least ten daily observations in the month. The panel yields 87,997 monthly returns for 894 companies over the 189 months from January 2010 to September 2025. Market capitalisation is the month end price times shares outstanding in rupiah for every firm, and all weights use the capitalisation of the previous month. Accounting characteristics enter with a six month lag. The risk free rate is the median yield of rupiah government bonds and sukuk with three to eighteen months to maturity.

Sector membership follows the IDX Industrial Classification adopted in 2021, which defines Technology as software and information technology services, technology hardware and electronic equipment. Forty tickers are classified as Technology and contribute 2,483 firm months. The number of technology firms with a return rose from six in 2010 to twenty three in 2021 and thirty six in 2025, and the sector's share of capitalisation rose from 0.2 per cent in 2010 to 6.2 per cent in 2022 and 4.5 per cent in 2025. Until 2017 one firm held between 72 and 89 per cent of the sector's capitalisation. Banks and other financial firms carry no sector label, so they remain in the market factor and in the sorted universe but not in the sector legs.

The factor is a long short portfolio rebalanced monthly. Its long leg holds every technology firm with weights proportional to lagged capitalisation, capped at a quarter of the leg, and its short leg holds the value weighted return of non technology firms in each technology firm's own size decile. Writing $w_{i,t}$ for the capped weight of technology firm i, $r_{i,t}$ for its return and $r_{b(i),t}$ for the return of its size matched benchmark, the factor is

$$\mathrm{TECH}_t = \sum_i w_{i,t} \left(r_{i,t} - r_{b(i),t} \right) \quad (1)$$

The market factor is the value weighted excess return of all firms. Size and value factors follow

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Fama and French (1993) with two by three sorts formed each June, and the momentum factor follows Carhart (1997) with monthly sorts on the twelve minus one return. Alternative constructions of TECH are used for robustness.

The technology beta of firm i at the end of month t is the slope on TECH in a regression of the firm's excess return on the market and TECH over the preceding thirty six months, requiring at least twenty four observations:

$$r_{i,s} - r_{f,s} = a_{i,t} + \beta_{i,t}^{M}\mathrm{MKT}_s + \beta_{i,t}^{T}\mathrm{TECH}_s + e_{i,s} \tag{2}$$

Each month from January 2012, firms above the twentieth percentile of lagged capitalisation are ranked on the lagged beta and formed into quintiles and deciles, equal weighted and value weighted, held for one month. The post ranking beta is the full sample loading of each portfolio's return on TECH, and its comparison with the mean pre ranking beta is the central diagnostic of the study. Fama and MacBeth (1973) regressions run each month across individual stocks:

$$r_{i,t} - r_{f,t} = \lambda_{0,t} + \lambda_{T,t}\beta_{i,t-1}^{T} + \lambda_{M,t}\beta_{i,t-1}^{M} + \gamma_t^{\top} Z_{i,t-1} + u_{i,t} \tag{3}$$

where $Z_{i,t-1}$ collects size, book to market, momentum, reversal, volatility and the share of zero return days, each winsorised and standardised within the month. All time series t statistics use the Newey and West (1987) covariance with the automatic bandwidth of Newey and West (1994).

Three sets of value weighted test assets are formed: ten sector portfolios, twenty five size and book to market portfolios and ten technology beta deciles. Over the 135 months in which all exist, the CAPM, three factor and four factor models, each with and without TECH, are evaluated with the Gibbons et al. (1989) statistic and the maximum squared Sharpe ratio of Barillas and Shanken (2017). Second pass regressions of mean excess returns on full sample betas,

$$\mu_p = \lambda_0 + \lambda^{\top}\beta_p + \eta_p \tag{4}$$

carry the Shanken (1992) correction, and the price of TECH risk is compared with the factor's sample mean. Persistence is the Spearman rank correlation between a firm's sorting beta and its own beta twelve and thirty six months later, and compression is the ratio of the post ranking to the pre ranking spread. Power is summarised by the number of months needed to detect the implied spread with eighty per cent power at the five per cent level,

$$T^{n} = \left(\frac{(1.96+0.84)\sigma_{HL}}{\Delta\beta^{post}\mu_{TECH}}\right)^{2} \tag{5}$$

where σ_{HL} is the standard deviation of the high minus low return, $\Delta\beta^{post}$ the post ranking beta spread and μ_{TECH} the factor mean.

4. Finding and Discussion

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4.1 The factor as a return

Table 1 reports the factors, and Figure 2 draws the technology leg, its benchmark and the factor. The main technology factor earns 0.64 per cent a month over 189 months with a standard deviation of 9.56 per cent, a t statistic of 0.81 and an annualised Sharpe ratio of 0.23. Its volatility is more than twice that of any standard factor, which range from 3.79 to 4.33 per cent. The plain value weighted construction earns 1.90 per cent with a t statistic of 1.85 and the version without the platform listings 2.21 per cent with 2.19, but for most of the sample these constructions are the return of one or two firms. Momentum earns 0.90 per cent a month with a t statistic of 2.46, consistent with Cakici et al. (2013) and Hanauer and Lauterbach (2019). Figure 2 shows that the technology leg tracked its benchmark until 2020, rose sharply into 2021, gave much of the gain back by 2024 and rose again in 2025.

Table 1. Factor returns, January 2010 to September 2025.

Factor	Mean (% per month)	t	SD (%)	Sharpe ratio, annualised	Months
MKT, market	0.29	(0.96)	4.22	0.24	189
SMB, size	0.67	(1.95)	3.79	0.61	183
HML, value	0.36	(1.23)	4.22	0.30	183
WML, momentum	0.90	(2.46)	4.33	0.72	189
TECH, main factor	0.64	(0.81)	9.56	0.23	189
TECH, plain value weighted	1.90	(1.85)	12.16	0.54	189
TECH, equal weighted	0.77	(1.11)	7.50	0.35	189
TECH, excluding platform listings	2.21	(2.19)	12.58	0.61	189

Note. Newey and West t statistics in parentheses. The main TECH factor holds technology firms with lagged value weights capped at 25 per cent of the leg and shorts the value weighted return of non technology firms in each technology firm's size decile.

(Source: Bloomberg, Indonesia Stock Exchange listed equities; processed by the author)

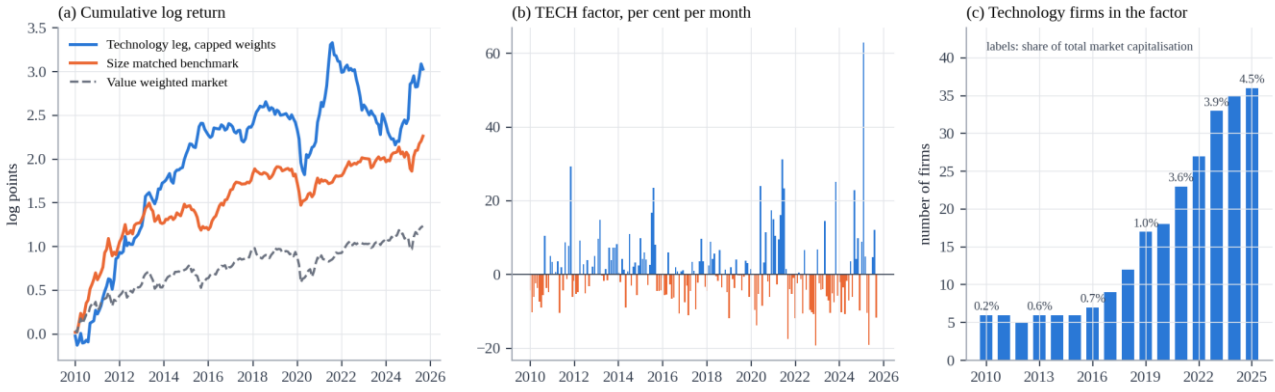


Figure 2. The technology leg, the TECH factor and the breadth of the sector. Panel (a)

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cumulates log returns of the capped technology leg, its size matched benchmark and the market; panel (b) is the monthly factor; panel (c) counts technology firms with the sector's share of capitalisation. (Source: Bloomberg, Indonesia Stock Exchange listed equities; processed by the author)

Table 2 asks whether TECH adds a mean return that the standard factors cannot deliver. Against the market alone the factor has an alpha of 0.82 per cent with a t statistic of 1.03 and a market loading of minus 0.63, so TECH moves against the market. Adding size and value leaves the alpha at 0.76 per cent, and adding momentum lowers it to 0.50 per cent with a t statistic of 0.69. In the reverse direction, HML, SMB and WML keep intercepts of 0.35, 0.70 and 0.82 per cent when TECH is added, with loadings on TECH between 0.03 and 0.06. H1 is therefore not supported: the technology factor is spanned by the standard factors, with a positive alpha that is indistinguishable from zero.

Table 2. Spanning regressions among the factors.

Dependent factor	Alpha (%)	MKT	SMB	HML	WML	TECH	R^2
TECH	0.822	−0.625					0.08
	(1.03)	(−2.15)					
TECH	0.763	−0.618	0.243	0.155			0.09
	(1.00)	(−2.18)	(1.12)	(0.89)			
TECH	0.499	−0.625	0.192	0.211	0.305		0.11
	(0.69)	(−2.18)	(0.95)	(1.34)	(1.72)		
HML	0.345	0.220	−0.082			0.031	0.06
	(1.27)	(2.59)	(−0.79)			(0.82)	
SMB	0.700	−0.197		−0.064		0.038	0.08
	(2.11)	(−2.47)		(−0.83)		(1.20)	
WML	0.815	0.063	0.149	−0.192		0.064	0.07
	(2.25)	(0.71)	(1.53)	(−1.98)		(1.60)	

Note. Each row regresses the dependent factor on the listed factors; Newey and West t statistics in parentheses. The first row covers 189 months and the others 183. (Source: Bloomberg, Indonesia Stock Exchange listed equities; processed by the author)

4.2 Portfolios sorted on the technology beta

Table 3 and Figure 3 report the central test of H2. The mean sorting beta runs from minus 0.51 in the lowest quintile to 0.53 in the highest, a spread of 1.04. The post ranking betas run from 0.02 to 0.13 across equal weighted quintiles and from minus 0.08 to 0.24 across value weighted ones, spreads of 0.12 and 0.31 with t statistics of 3.21 and 5.88. The high minus low return spread is minus 0.12 per cent a month equal weighted with a t statistic of minus 0.36 and 0.28 per cent value weighted with 0.54. Against the three factors plus TECH the spread alphas are minus 0.39 per cent equal weighted with a t statistic of minus 1.57 and zero value weighted. The beta sort thus produces a reliable spread in exposures and no measurable spread in returns.

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Table 3. Quintile portfolios sorted on the lagged technology beta.

Portfolio	Pre ranking beta	Post ranking beta	Excess return (%)	CAPM alpha (%)	Three factor plus TECH alpha (%)
EW, Low	−0.51	0.019 (0.46)	0.558 (1.10)	0.421 (1.25)	0.022 (0.09)
EW, 2	−0.17	0.043 (1.43)	0.453 (1.07)	0.339 (1.36)	−0.059 (−0.36)
EW, 3	−0.03	0.034 (1.26)	0.207 (0.51)	0.103 (0.41)	−0.242 (−1.34)
EW, 4	0.11	0.051 (2.11)	0.359 (0.86)	0.238 (0.96)	−0.129 (−0.76)
EW, High	0.53	0.134 (4.41)	0.438 (0.81)	0.317 (0.78)	−0.362 (−1.91)
EW, High minus low	1.04	0.116 (3.21)	−0.120 (−0.36)	−0.104 (−0.31)	−0.385 (−1.57)
VW, Low	−0.51	−0.076 (−1.58)	0.083 (0.20)	−0.046 (−0.16)	−0.054 (−0.19)
VW, 2	−0.17	−0.011 (−0.31)	0.048 (0.13)	−0.061 (−0.29)	−0.084 (−0.39)
VW, 3	−0.03	−0.008 (−0.30)	0.359 (0.87)	0.224 (1.01)	0.199 (0.93)
VW, 4	0.11	0.060 (2.26)	−0.063 (−0.17)	−0.201 (−1.10)	−0.224 (−1.28)
VW, High	0.53	0.238 (4.77)	0.360 (0.74)	0.225 (0.63)	−0.056 (−0.18)
VW, High minus low	1.04	0.315 (5.88)	0.277 (0.54)	0.271 (0.53)	−0.002 (−0.00)

Note. Equal weighted (EW) and value weighted (VW) quintiles formed monthly from January 2012 on the beta estimated over the preceding thirty six months, about 63 firms each. Newey and West t statistics in parentheses.

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(Source: Bloomberg, Indonesia Stock Exchange listed equities; processed by the author)

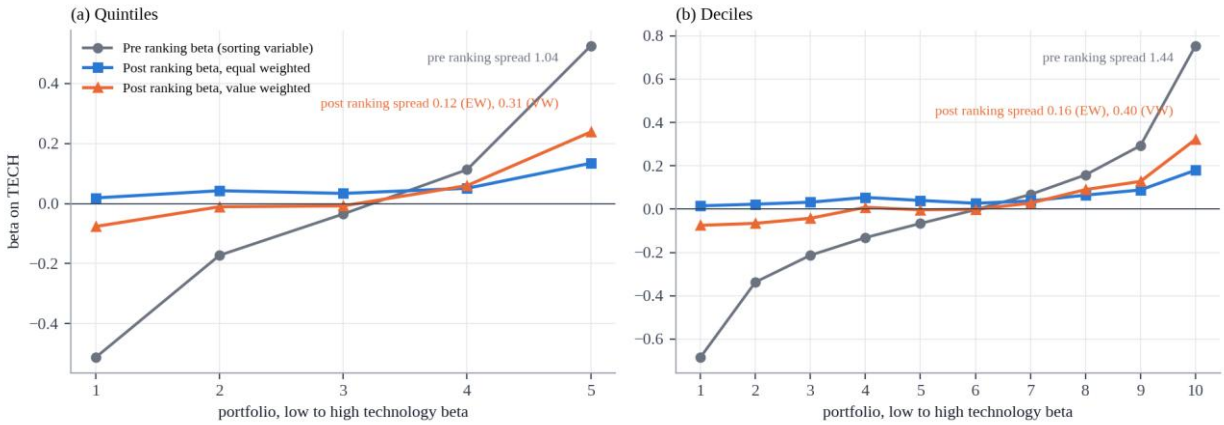


Figure 3. Pre ranking and post ranking technology betas. The grey line is the mean sorting beta of each portfolio; the coloured lines are the full sample loadings of the portfolios' subsequent returns on TECH. (Source: Bloomberg, Indonesia Stock Exchange listed equities; processed by the author)

Table 4 reports the Fama and MacBeth regressions. The technology beta carries coefficients between minus 0.03 and minus 0.06 per cent per cross sectional standard deviation, with t statistics between minus 0.22 and minus 0.61, whichever controls are included. Size, momentum and within month volatility carry the expected signs, with t statistics of 1.88 or more in absolute value. The technology sector dummy earns 0.91 per cent a month alone with a t statistic of 1.33 and 0.25 to 0.27 per cent with controls. H2 is not supported at the level of individual stocks either, although the sign of the beta coefficient is the one the theory predicts.

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Table 4. Fama and MacBeth regressions of monthly excess returns.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Technology beta	−0.027	−0.043	−0.046	−0.061			−0.045
	(−0.22)	(−0.37)	(−0.45)	(−0.61)			(−0.40)
Market beta		0.158	0.133	0.033		0.062	0.083
		(1.14)	(0.94)	(0.25)		(0.44)	(0.60)
Log size			−0.239	−0.257		−0.248	−0.262
			(−1.95)	(−2.24)		(−1.88)	(−2.00)
Book to market			0.192	0.188		0.104	0.103
			(1.93)	(1.81)		(0.88)	(0.88)
Momentum			0.556	0.559		0.390	0.369
			(3.29)	(3.33)		(2.27)	(2.15)
Reversal				0.160		0.084	0.074
				(0.84)		(0.39)	(0.36)
Volatility				−0.343		−0.447	−0.435
				(−2.72)		(−3.21)	(−3.13)
Zero return days				0.053		0.047	0.049
				(0.37)		(0.28)	(0.29)
Technology dummy					0.913	0.247	0.271
					(1.33)	(0.31)	(0.34)
Months	165	165	165	165	189	158	158

Note. Characteristics are lagged, winsorised and standardised within the month, so a coefficient is the return in per cent per cross sectional standard deviation; the sector dummy is unstandardised. Newey and West t statistics in parentheses. (Source: Bloomberg, Indonesia Stock Exchange listed equities; processed by the author)

The time series and second pass tests point the same way. On the union of 45 test portfolios the Gibbons et al. (1989) statistic is 0.86 for the three factor model and 0.84 with TECH added, and the maximum squared Sharpe ratio of the factors rises from 0.030 to 0.033 a month, against the 0.026 that momentum adds. The price of TECH risk on all 45 portfolios is 0.84 per cent a month with a Shanken corrected t statistic of 0.80, close to the factor's own mean of 0.76 per cent over these months. Across the four sets of test assets the price ranges from minus 0.39 to 1.38 per cent and always lies in an interval that contains zero, which is how Lewellen et al. (2010) advise reading such estimates.

4.3 Compression, persistence and power

Table 5 explains why a well defined factor prices nothing measurable. Twelve months after formation, when the estimation windows still overlap by twenty four months, the rank correlation between a firm's technology beta and its own later beta is 0.61. Thirty six months

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after formation, when the windows share nothing, the correlation is 0.09 against 0.28 for the market beta from the same regressions, and only 27 per cent of the top quintile remains there. The ratio of post ranking to pre ranking spread is 11 per cent for equal weighted portfolios and 28 to 30 per cent for value weighted ones. At the factor's mean, the post ranking exposures imply return spreads between 0.07 and 0.25 per cent a month, while the minimum detectable spread over 165 months is between 0.55 and 1.19 per cent. Detecting the implied spread with eighty per cent power would require between 600 and 1,791 years of monthly data.

Table 5. Compression of the technology beta and the power of the sort.

Sort	Pre ranking spread	Post ranking spread	Ratio (%)	Implied spread (%)	Actual spread (%)	Minimum detectable (%)	Years needed
Quintile, EW	1.04	0.116 (3.21)	11	0.074	−0.120 (−0.36)	0.55	1,756
Quintile, VW	1.04	0.315 (5.88)	30	0.201	0.277 (0.54)	0.87	600
Decile, EW	1.44	0.164 (3.38)	11	0.105	−0.214 (−0.48)	0.78	1,791
Decile, VW	1.44	0.397 (4.98)	28	0.253	−0.260 (−0.38)	1.19	709

Note. The implied spread is the post ranking beta spread times the factor mean of 0.64 per cent a month; the minimum detectable spread is at the five per cent level over 165 months; years needed are from equation (5) with eighty per cent power. (Source: Bloomberg, Indonesia Stock Exchange listed equities; processed by the author)

The compression has two sources. The first is estimation error in a slope on a factor whose monthly standard deviation is near ten per cent and whose mean is carried by a few months, estimated from thirty six observations on stocks whose own returns have a standard deviation of sixteen per cent, which is the regression to the mean that Blume (1975) and Vasicek (1973) describe. The second is that true exposures drift as the sector changes from a handful of firms to forty. A sixty month window and a Dimson (1979) adjustment leave the post ranking spread at 0.10, which points toward the second source.

4.4 Where the exposure lives

Table 6 shows which sectors load on the factor. The technology sector portfolio loads on TECH at 0.95 with a t statistic of 9.36, and adding TECH raises the explained share of its variance from 0.03 to 0.57. Consumer Cyclicals loads positively at 0.07, while Infrastructures and Energy load negatively at minus 0.11 and minus 0.20. These loadings mirror the commodity and interest rate cycles of 2021 and 2022. Transportation and Logistic, where ride hailing and delivery platforms compete most directly with listed incumbents, loads at 0.02 with a t statistic of 0.32. H3 is therefore not supported: exposure is concentrated in the sector itself, and incumbent sectors show no displacement pattern.

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Table 6. Sector portfolios and the technology factor.

Sector	Excess return (%)	Beta on MKT	Beta on TECH	R^2, CAPM	R^2, CAPM plus TECH
Technology	2.14 (2.03)	1.05	0.950 (9.36)	0.026	0.568
Consumer Cyclicals	0.44 (0.75)	1.12	0.068 (2.42)	0.433	0.441
Property and Real Estate	0.57 (0.93)	1.27	0.055 (0.93)	0.434	0.438
Industrials	0.20 (0.41)	1.10	0.023 (0.50)	0.491	0.492
Transportation and Logistic	−0.29 (−0.39)	1.14	0.019 (0.32)	0.262	0.263
Healthcare	0.73 (1.55)	0.73	−0.010 (−0.33)	0.302	0.303
Consumer Non Cyclicals	0.14 (0.39)	0.71	−0.019 (−0.53)	0.500	0.502
Basic Materials	0.43 (0.82)	1.20	−0.069 (−1.47)	0.503	0.510
Infrastructures	0.32 (0.75)	0.98	−0.114 (−2.01)	0.423	0.447
Energy	0.25 (0.42)	0.88	−0.197 (−2.74)	0.310	0.367

Note. Value weighted sector portfolios of the microcap screened universe regressed on the market alone and on the market and TECH. Newey and West t statistics in parentheses. (Source: Bloomberg, Indonesia Stock Exchange listed equities; processed by the author)

At the firm level, 8.7 per cent of 699 non technology firms with at least thirty six months of data load on TECH beyond a t statistic of 1.96 in absolute value, against 5 per cent expected under the null. Of these, 6.6 per cent load positively and 2.1 per cent negatively. Among the 25 technology firms with enough data, 68 per cent exceed the threshold and the median loading is 0.50. The exposure therefore lives in the sector and in a small group of firms that behave like technology firms without carrying the label.

Monthly cross sectional regressions of the technology beta on firm characteristics support H4. Alone, Tobin's q enters with a coefficient of 0.023 per standard deviation and a t statistic of 3.81, and book to market enters with minus 0.015 and a t statistic of minus 3.72. With the sector dummy, size, the market beta, volatility, profitability and zero return days held fixed, the coefficients are 0.021 and minus 0.011 with t statistics of 3.46 and minus 3.18. Its economic size, about 0.02 of a beta per standard deviation of q against a cross sectional standard deviation of 0.43, is the compression result seen from the other side.

4.4 Every sector through the same procedure

To check whether the procedure itself drives these results, for each of the ten sectors a factor is built exactly as TECH is built, and firms outside the sector are sorted on their rolling beta to it. Figure 4 reports the result. The technology factor has the largest standard deviation of the ten and the smallest pre ranking beta spread, 0.99, and its equal weighted post ranking spread of

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0.05 lies inside a range from minus 0.08 to 0.28. Its equal weighted spread alpha of minus 0.22 per cent with a t statistic of minus 0.84 lies inside a range from minus 0.28 to 0.43 per cent. Across ten sectors and two weightings the procedure produces two significant spreads, neither of them technology, so compression is a property of rolling betas on sector returns in this market.

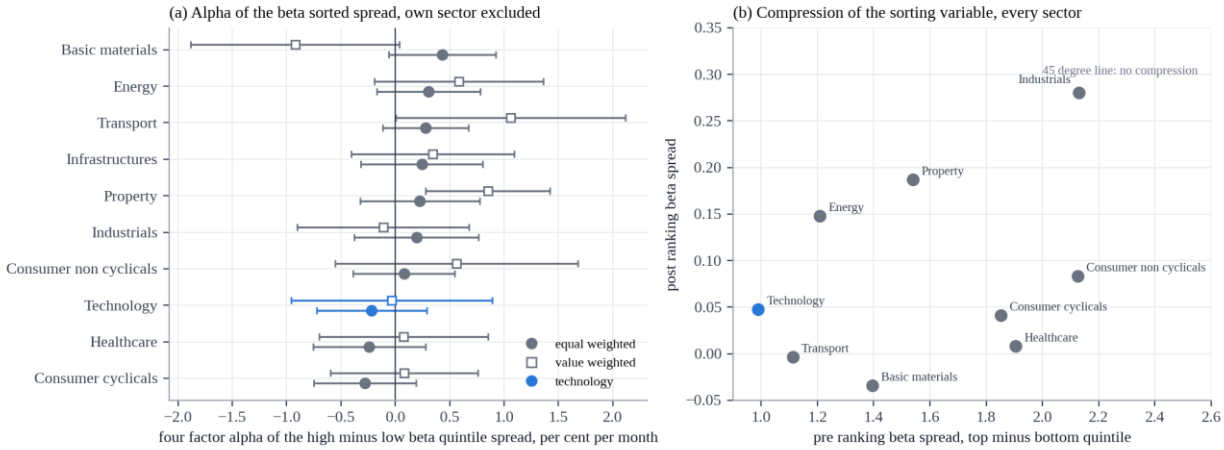


Figure 4. Ten sector factors through the same procedure. Panel (a) gives the four factor alpha of the high minus low spread on the rolling beta to each sector's factor with 95 per cent bands; panel (b) plots post ranking against pre ranking beta spreads. (Source: Bloomberg, Indonesia Stock Exchange listed equities; processed by the author)

The results hold across subperiods and alternative procedures. From 2012 to 2018, when the technology leg held six firms on average, the equal weighted spread alpha was minus 0.37 per cent with a t statistic of minus 1.09, and from 2019 to 2025 it was minus 0.33 per cent with minus 1.11. Removing technology firms from the sorted universe lowers the equal weighted post ranking spread to 0.07, and across ten variations of the procedure the post ranking spread never exceeds half of the pre ranking spread. The value weighted post ranking spread rose from 0.12 before 2019 to 0.45 since 2021, which indicates that the largest listings have begun to move with the sector.

Read jointly, the results describe a factor that is real as a description of one sector's return, that relates to growth opportunities as the theory predicts, and whose exposures outside the sector are still too small and too unstable to be priced in a 165 month sample. Investment specific shocks in the sense of Papanikolaou (2011) require a sector whose output is an input to the rest of the economy, so that its shocks change the price of capital that other firms buy. For most of the sample the Indonesian technology sector was a small group led by one firm, and later a few platforms whose returns reflected their own listing histories. The displacement mechanism of Gârleanu et al. (2012) requires the same breadth from the other direction, since incumbents must lose rents to innovators for their valuations to move against them. As digital services become embedded in the production of other firms, the post ranking spread should widen, the

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sector loadings should disperse and the required sample should shrink from centuries toward decades.

5. Conclusion

This study takes the central observable of the theories of technology risk, the return of the technology sector in excess of the rest of the market, to an exchange on which that sector was created during the sample. The factor is a well defined return of 0.64 per cent a month that the market, size, value and momentum factors span. Its exposures are concentrated in the technology sector and in a small group of similar firms, and the rolling betas that would carry a premium into portfolio sorts lose between seven and nine tenths of their dispersion at formation. The prediction that exposure rises with Tobin's q and falls with book to market holds in sign, and technology sits within the range of the other nine sectors on every diagnostic.

The study adds a boundary condition to the literature on technology risk. Propagation of a sector's shocks through other firms' valuations requires that the sector's output enter their production or that its rents come from them, and the Indonesian technology sector of 2010 to 2025 is approaching that position rather than already occupying it. For investors and fund managers, the evidence indicates that technology exposure in Indonesia is at present a sector bet rather than a systematic risk to be hedged across the market. For regulators and the exchange, continued broadening of the technology sector and deeper integration of digital services into other industries are the conditions under which the sector becomes a priced driver of national competitiveness. For researchers, the post ranking spreads, beta persistence and required sample lengths reported here form the baseline against which the Indonesian technology factor can be tested again as the sector grows.

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