ARTIFICIAL INTELLIGENCE ADOPTION AND BANK SHAREHOLDER VALUE: EVIDENCE FROM ASIA-PACIFIC REGION

ÁP DỤNG TRÍ TUỆ NHÂN TẠO VÀ GIÁ TRỊ CỔ ĐÔNG TRONG NGÀNH NGÂN HÀNG: BẰNG CHỨNG TỪ KHU VỰC CHÂU Á - THÁI BÌNH DƯƠNG

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ABSTRACT

Artificial intelligence-based applications in Asia-Pacific banks have been dynamically occurring over the last decades, especially during the surge of the COVID-19 pandemic. However, little is found to assess the net impacts of AI use for bank shareholder value creation although the main purpose of bank management is to enrich shareholder wealth. Using the shadow cost of equity and control function approaches, we found that in general, using artificial intelligence decreases shareholders' economic value for banks' private shareholders because of higher capital charges after controlling for several factors. The results remain unchanged given a set of robustness checks. Meanwhile, we discovered that the impacts of artificial intelligence adoption vary across bank sizes and the impacts of the COVID-19 pandemic. Altogether, our study contributes to the framework related to shareholder value in Asia-Pacific banking by clarifying the divergence between profitability and shareholder value creation.

Keywords: Artificial intelligence use, Commercial banks, Shareholder values, Shadow price of equity, Control function approach, Asia-Pacific.

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JEL classification: G21, N25, O33.

TÓM TẮT

Việc ứng dụng trí tuệ nhân tạo (AI) ở các ngân hàng thuộc khu vực châu Á – Thái Bình Dương đã và đang diễn ra mạnh mẽ trong những thập kỷ gần đây, đặc biệt là trong làn sóng đại dịch COVID-19. Tuy nhiên, dù rằng mục đích chính của công tác quản trị ngân hàng là tối đa hóa giá trị cổ đông, rất ít nghiên cứu tập trung vào đánh giá tác động thuần của việc sử dụng AI trong việc tạo ra giá trị kinh tế cho cổ đông ngân hàng. Sử dụng mô hình chi phí chìm vốn cổ phần (Shadow cost of equity) cùng phương pháp CFA (control function approaches), tác giả nhận thấy rằng, nhìn chung, việc sử dụng AI làm giảm giá trị kinh tế cho cổ đông ngân hàng, chủ yếu do việc cổ đông yêu cầu chi phí vốn đầu tư (capital charge) cao hơn. Kết luận này vẫn không thay đổi sau hàng loạt phép kiểm định. Đồng thời, nghiên cứu còn chỉ ra mối tương quan giữa việc sữ dụng AI và giá trị cổ đông thay đổi theo quy mô ngân hàng và ảnh hưởng của đại dịch COVID-19. Từ đó, nghiên cứu này ủng hộ quan điểm "lợi nhuận" và "giá trị cổ đông" là khác nhau.

Từ khóa: Ứng dụng AI, Ngân hàng thương, Giá trị cổ đông, Chi phí chìm vốn cổ phần, CFA.

1. Introduction

Coined in 1956 by American computer scientist John McCarthy, the term artificial intelligence (AI) can be understood as "the application of the computational tool to address tasks traditionally requiring human sophistication (Financial Stability Board, 2017)". Reliable media sources inform huge potential and surges in AI adoption[1]. From

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an academic stance, several authors proved that AI brings to commercial banks things beneficial to profitability, such as cost reductions (Butaru et al., 2016; Kumar et al., 2019) and revenue growth (Alfaro et al., 2019), and risk management (Cheng & Qu, 2020).

Against the backdrop, the question of whether AI usage affects shareholder value creation remains unclear. This research question is critical because the main goal of bank management is to enrich shareholder wealth, not only ensure profitability. From a bank viewpoint, equity capital is a productive factor and thus has a cost (Fiordelisi & Molyneux, 2006). A bank may increase its profitability by risk-taking, but private shareholders may charge a higher rate of return. In case increases in operating inadequately offset these capital charges, bank management fails to increase shareholder wealth despite successfully ensuring profitability. Moreover, the shift to AI uses inevitably contains new risks, such as cyber-attacks, data thefts, and customer apprehension of privacy data exploitation. Second, we selected the Asia-Pacific region as the research site because most of the Asia-Pacific countries weathered the global financial crisis of 2007-2008 quite successfully with quick policy responses, maintaining official reserves, and balancing corporate sectors and banking systems. Moreover, several Asia-Pacific banks recently started to embrace AI, and local authorities also provide support and guidance. Therefore, we argue that this region offers a particularly ideal setting in which to research the relationship between shareholder value and AI adoption. Lensing to the Asia-Pacific region, Cheng & Qu (2020) is the only one discussing the impacts of AI uses in the commercial banking context and found that AI use reduces credit risks. Concerning shareholder value creation, Radić (2015) is the only one to use the shadow price of equity to include non-listed banks in the analysis. Third, we chose commercial banks as research entities because commercial banking is the spinal of the economy in providing credit. Meanwhile, this industry is highly regulated, therefore uncertainty may arise regarding whether AI usage is meaningful, and therefore research on such topics is worthy.

We set an unbalanced panel of 302 commercial banks in 19 economies across Asia-Pacific from 2015 to 2020. To address the potential endogeneity caused by unobserved factors, we adopted the control function approach (Wooldridge, 2015). Shareholder value creation is measured using the economic shareholder value-added approach using the shadow cost of equity as a proxy for the cost of capital (Radić, 2015). Interestingly, we found that adopting AI helps banks increase profits, but their shareholders charge higher costs of equity. As a result, after adopting AI, bank shareholders' economic value decreases. These findings are robust to alternative estimations for the cost of capital, dynamics in short and long-run effects, and alternative econometric methods used to address endogeneity and sample selection.

We further analyze whether the nexus between shareholder value creation and AI adoption varies across bank size and the impacts of the current COVID-19 pandemic. The results of this heterogeneity showed that

[1] International Data Corporation forecasted that 60 percent of Asia-Pacific banks will use AI and machine learning to make data-driven decisions (International Data Corporation, 2020). McKinsey & Company claimed that AI can unblock USD 1 trillion of incremental value for banks (Biswas et al., 2020).

larger banks can escape from the trade-off between profitability and capital charges. Moreover, banks operating in the higher severity level add value to shareholders because they require a lower cost of capital.

Our study poses theoretical and practical implications. First, our findings contribute to making the distinction between shareholder value creation and profitability evident. While profitability gained by AI can justify the associated risks, we showed the possibility of negative economic values for shareholders. Second, our findings are geared toward a risk-return tradeoff framework in the literature on IT use (Ciciretti et al., 2009; He et al., 2020). To our knowledge, this is the first attempt to investigate the impacts of artificial intelligence shareholder value. Third, understanding our paper contributes to theoretical development to construct the determinants of shareholder value in banking (Fiordelisi & Molyneux, 2006, 2010; Fu et al., 2014b; Radić, 2015).

The rest of our paper is organized as follows. First, we present theoretical and related works to ours. Then, we outline our research design and econometric methods. After reporting the empirical on the baseline and additional analyses, we discuss theoretical and practical implications to end this current article.

2. Literature Review

2.1. Shareholder value theory

Shareholder value theory proposes three strategies that banks can follow to target shareholder value creation (SVA): increasing the expected cash flows to equity, reducing the hurdle rate, and matching as closely as possible their financing sources with their investments (Fiordelisi & Molyneux, 2006). Given these strategies, the literature suggests several factors affecting SVA for commercial banks.

First, banks can increase SVA by *satisfying customers*. Generally, customer satisfaction links to increasing bank images and reputations and higher confidence in banks. Therefore, banks are more able to diversify their customer base and cross-selling and reduce the amortization period of fixed investments and advertising expenses (Fiordelisi & Molyneux, 2006). If properly managed, these sequential steps can become a virtuous circle leading to better economic performance and, ceteris paribus, to increased bank shareholder value. Fiordelisi & Molyneux (2006), based on Customer Life Time Value and Value at Risk of Competition models, suggest two strategies for banks to create shareholder value through the value of customers (ceteris paribus): reducing the percentage of customers at risk of leaving the bank in any of its customer segments and increasing the expected profitability growth rate for any of its customer segments.

Second, banks may focus on *boosting efficiency* to cut costs or generate profits to increase SVA. Improving technical efficiency helps banks obtain a higher level of outputs from a given set of inputs or reduce inputs for a given target of outputs. In both cases, the bank will obtain a higher net income since it will benefit from higher operating income or lower operating costs. Ceteris paribus, banks create values for their shareholders. In addition, improving allocative efficiency poses opportunities for banks to obtain higher net operating profits after tax due to the use of inputs in optimal proportions, given their respective prices and production technology (Fiordelisi & Molyneux, 2006). The literature evidenced a positive link between bank efficiency and

SVA (Fiordelisi & Molyneux, 2010; Fu et al., 2014b; Radić, 2015).

Third, banks can take advantage of their *financial structure* to create shareholder value by impacting the cost of capital. The basic principle of corporate finance states that an enterprise's financial structure can be viewed as optimal if it ensures the minimum cost of capital, considering equity and debt capital. Banks can minimize their cost of capital in serval ways, such as reducing operational risks (as both costs of equity and cost of debts are associated with banks' risks), reducing operating leverage (as it is positively related to banks' risks), changing the financing mix (i.e. the mix of equity and debts used) and type (as it reduces the liquidity risks and the probability of default). Focusing on the selection of the optimal financial mix (or financial structure), Fiordelisi & Molyneux (2010) documented a significantly positive relationship between financial leverage and shareholder value creation in the European banking industry.

2.2. The impacts of AI adoption

From the view of shareholder value theory, adopting AI is expected to impact SVA, but the sign remains clear. Casu et al. (2006) stated that four business angles make commercial banks unique: products/services, involved activities, customer targeting, and implications that the previous three have for customer relationships. Hinging on these aspects, we address both the benefits and drawbacks of AI use.

For the products/services, different banks often offer fairly similar products/services (Königstorfer & Thalmann, 2020). In order to sell and market their products, banks often use customer relationship management (CRM) as a means. By adopting AI, banks could utilize internal data (customer profile, transaction history, and others) to scheme for designing products/services. As such, the products become more customer-tailored. Moreover, AI-based applications serve clients with breakthrough and 24/24 services, which supplement the physical branches. Alfaro et al. (2019) showed that sales made to SMEs by branches equipped with AI were double compared to offices without AI. However, because the CRM remains its essence in customer targeting, being more dependent on digital technologies makes banks more fragile as fewer client-bank interactions. Königstorfer & Thalmann (2020) argued that employees' emotional intelligence could more easily relate to people in "life events" situations, such as divorce, the death of a parent or a spouse, or losing jobs, than AI.

From the activities aspects, there are three main activities that commercial banks strictly concentrate on lending, deposits, and payment processing. From the lending side, AI allows banks to utilize previously unused types of data to lend profitably. Using data on customers' credit scores and transactions history through AI helps banks better evaluate the quality of loans, and realize the chances of default, and creditworthiness (Financial Stability Board, 2017; Königstorfer & Thalmann, 2020; Lessmann et al., 2015). Sigrist & Hirnschall (2019) proposed an algorithm that uses social media and online behavior data for default prediction. Chen & Huang (2011) showed that artificial neural networks can forecast credit default. Xiong et al. (2013) built a personal bankruptcy prediction system running on credit card data that overtakes the bureau's credit scoring. The analysis of customers' behaviors, profiles, behaviors, and interactions with banks' offerings using AI-based systems also helps banks detect fraud (Financial Stability Board, 2017). Jadhav et al. (2017) showed that AI algorithms can be used to spot financial statement fraud and fraudulent behavior in online banking. However, despite fostering hard information-based, the use of AI tools also lessens soft information-based products, such as loans to small-to-medium-size enterprises (Boot et al., 2021). From the payment processing side, AI-based applications help banks detect money laundering in transactions (Jadhav et al., 2017; Zhang & Trubey, 2019). But, the inclusion of AI may lay the ground for cyber risks because of malicious use (Brundage et al., 2018). (Boot et al. (2021) argued that the rise of AI and machine learning gives rise to new risks because they have no underlying models. From the deposit side, AI can be used to seek customers for long-term deposit plans, such as in Martens et al. (2016) methods. However, the use of AI may attract less loyal customers (because of the fewer physical interactions between banks and clients) and raise liquidity risks for banks.

In accordance with these activities, costs are imperative. Using AI systems for operations may cut the number of employees, which helps save wages and compensation expenses. Butaru et al. (2016) estimated that cost savings that banks achieve from the use of machine learning models range from 9% to 76%. Adopting AI can also help banks avoid human errors, which are the major cause of financial data breaches (Verizon, 2019). Kumar et al. (2019) stated that support vector machine learning techniques reduce costs by reducing the amount of time needed to evaluate potentially fraudulent transactions and enhance the decision quality of human employees by reducing their workloads. However, banks must spend significantly on AI-related projects, and need time for trials/tests before adopting. Given that profits equal revenue minus costs, these increasing operating costs directly hit the short-term profits. Beccalli (2007) proved that IT investment has little relationship with improved bank profitability. Uddin et al. (2020) found that cyber spending adversely affects banks' financial stability.

From the customer aspect, commercial banks could enhance customer experience by offering more customer-centric products and/or services. Thence, they become more competitive to fight against rivals, such as Fintech companies, and non-bank financial institutions. However, the overuse of user data may increase the possibility of data theft, and raise policy issues related to data privacy and data protection (Financial Stability Board, 2017). In this sense, customers are more concerned about their privacy, therefore their experience may go down. PwC (2019) survey reports that customers' apprehension and trust in AI for their privacy is one of the major for banks to promote AI adoption. Besides, privacy is an issue for collecting and analyzing customer data (Aziz & Dowling, 2019; Martens et al., 2016).

From the aforementioned literature, we form two opposite hypotheses as follows.

H1: AI usages *positively* affect shareholder value creation

H2: AI usages *negatively* affect shareholder value creation

3. Methodology

3.1. Econometric models

We use the following empirical model to analyze the effects of AI adoption on shareholder value creation:

$$EVA_{it} = \alpha_0 + \alpha_1 D_{AI,it} + \beta_1 X_{1,it} + \beta_2 X_{2,jt} + \mu_t + \mu_i + \varepsilon_{it} \quad (1)$$

For Eq. (1), EVA_{it} is the measurement of economic values added. Our variable of interest is $D_{AI,it}$ which denotes the measurement of AI adoption. $X_{1,it}$, and $X_{2,it}$ are vectors of control variables at a bank and country level, respectively. Further, we included bank-fixed effects and year-fixed effects.

We noted that there are factors affecting AI adoption and shareholder value creation, therefore causing potential endogeneity. For example, the unobserved managerial ability may attempt to raise shareholder value creation by adopting AI. It may drive a negative correlation between AI adoption and the error term in Eq. (1). To address this issue, we used the control function approach (Wooldridge, 2015). Following the literature, we specify the reduced-form Probit model for AI adoption as follows:

$$D_{AI,it} = \delta_0 + \delta_1 X_{1,it} + \delta_2 X_{2,jt} + \delta_3 Z_{it} + \mu_t + \mu_i + e_{it} \quad (2)$$

In Eq. (2), we included a set of variables used in Eq. (1), which are the vector X_{it}, year fixed effects, and bank fixed effects. The instrumental variables Z_{it} consist of factors driving AI adoption suggested in the literature. These are five dimensions: size, financial performance, business strategy, capital adequacy, competition, and demographics. Details are presented in Appendix A.

Assuming that $\{\varepsilon_{it}; e_{it}\}$ are jointly normally distributed, we derive the following relationship:

$$E\left(\varepsilon_{it} | D_{AI,it}, X_{1,it}, X_{2,jt}\right) = E\left(\varepsilon_{it} | e_{it}, X_{1,it}, X_{2,jt}\right) = E\left(\varepsilon_{it} | e_{it}\right) = \gamma GR_{it} \quad (3)$$

Relationship (3) suggests that GR_{it} can be incorporated in Eq. (1) to control the potential endogeneity. The definition of generalized residuals GR_{it} is as follows (the function $\phi(.)$ and $\Phi(.)$ are the probability density function and cumulative distribution function of standard normal distribution, respectively).

$$GR_{it} = D_{AI,it} \times \frac{\phi(\widehat{D_{AI,it}})}{\Phi(\widehat{D_{AI,it}})} + (1 - D_{AI,it}) \times \frac{-\phi(\widehat{D_{AI,it}})}{1-\Phi(\widehat{D_{AI,it}})} \quad (4)$$

Three equations (1), (2), and (3) suggest the following procedure. First, we estimated Eq. (2) to generate GR_{it} defined in (4). Then, we added GR_{it} to Eq. (1) as a proxy for unobserved factors as follows.

$$EVA_{it} = \alpha_0 + \alpha_1 D_{AI,it} + \beta_1 X_{1,it} + \beta_2 X_{2,jt} + \gamma GR_{it} + \mu_t + \mu_i + \varepsilon_{it} \quad (5)$$

Using the control function approach is advantageous in some respects. First, it is simple to estimate because the least-squares fitting of Eq. (5) produces a consistent estimate of α_1. Second, coefficient γ can serve as a heterogeneity-robust Hausman test for the null hypothesis that $D_{AI,it}$ is exogenous (Wooldridge, 2015). Third, a positive (negative) γ indicates that banks that create more economic value for shareholders are more (less) likely to adopt AI. Finally, it is more efficient than two-stage least-squares estimation (2SLS) concerning adding interaction terms of our instruments and additional variables.

3.1.1. Shareholder value creation

We followed Stewart's methods to use economic values added to proxy for shareholder value creation (Fiordelisi & Molyneux, 2006, 2010; Fu et al., 2014b; Radić, 2015). Under this approach, a bank is considered to generate value for shareholders if its operating profits exceed the capital charges. Specifically, we defined economic values added as follows.

$$EVA_{it} = (NOPAT_{it} + LLP_{it}) - (CI_{it} \times K_{it}) \quad (6)$$

In Eq. (6), we adjusted the net operating profits after tax $NOPAT_{it}$ by adding back loan loss provisions LLP_{it}. The invested capital CI_{it} is proxied by the total amount of Tier-1 and Tier-2 capital. In order to include both non-listed and listed banks in our analysis, we shifted our methods used to estimate the cost of capital to the shadow cost of equity approach (Radić, 2015). Details are presented in Appendix B.

3.1.2. Artificial Intelligence Adoption

We constructed one dummy variable taking the value of one for a bank adopting AI, and zero otherwise, to measure AI adoption. Banks adopt AI in several forms for basics, such as operations (face recognition, robotic process automation, robotic analysis, virtual assistants), risk management (Robo-advisors, virtual assistants), and customer services (chatbots). Fig. 1 shows that AI adoption increases over time. From the beginning of 2015, the number of adopters is less than non-adopters, but it rapidly takes over from 2019.

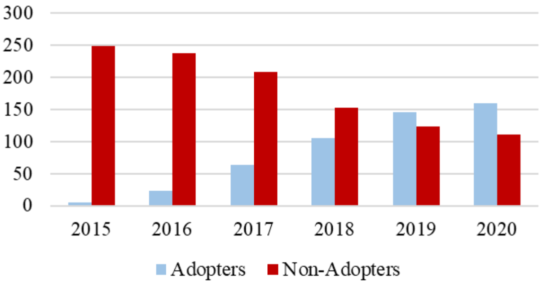

Figure 1. AI adopters through the years

3.1.3. Controls

Following the literature, we controlled several factors affecting shareholder value creation, including bank size, risk exposure, efficiency, and financial leverage (Fiordelisi & Molyneux, 2006, 2010; Fu et al., 2014b; Radić, 2015).

3.2. Data and Sample

We frame the sample based on the availability of data used to estimate shadow costs of equity. Financial data were mainly collected from the Capital IQ database and later complemented by data from annual reports. The unique feature of our dataset is the bank-specific information regarding AI adoption. It was hand-collected from annual reports. The macro and demographic data were drawn from the World Bank database and the Bureau of Statistics. Altogether, we achieved an unbalanced panel of 302 commercial banks around 19 Asia-Pacific markets from 2015 to 2020.

Table 1. *Distribution*

Areas	Market/Year	2015	2016	2017	2018	2019	2020	Total
Asia-Pacific Developed Markets	Hong Kong	14	14	14	14	14	14	84
	Australia	7	9	9	8	9	9	51
	Japan	9	5	9	6	11	8	48
	Korea, South	8	8	9	6	5	5	41
	New Zealand	2	3	3	4	4	3	19
	Singapore	3	2	2	3	3	3	16

Asia-Pacific Developing Markets	China	70	78	79	75	81	83	466
	Taiwan	32	31	32	32	32	33	192
	Indonesia	23	22	26	26	22	21	140
	Bangladesh	23	23	23	23	23	22	137
	Malaysia	14	14	14	13	14	14	83
	Thailand	12	13	13	13	13	13	77
	Pakistan	13	12	12	10	10	12	69
	Philippines	8	9	9	9	9	9	53
	India	9	8	8	8	8	9	50
	Sri Lanka	4	4	5	5	6	6	30
	Georgia	3	3	3	2	3	3	17
	Armenia	0	2	2	2	2	2	10
	Macau	0	0	0	0	0	1	1
	Total	254	260	272	259	269	270	1584

4. Research results

4.1. Basic statistics

Table 2 reports the descriptive statistics of dependent and independent variables. On average, both three shareholder value measures are negative, suggesting that most banks in the sample fail to add value for their private shareholders over the sample period. This trend was also prior studies in Asia-Pacific (Fu et al., 2014b). There are approximately 32% of observations have D_{AI}=1.

Table 2. *Descriptive statistics*

EVA = Economic value added; NOPAT = Net profits after tax; CACH = Capital charges; D_{AI} = AI adoption; NPL = Credit risks; LDR = Liquidity; MRI = Market risks; PE = Profit efficiency; CE = Cost efficiency; LEV = Financial leverage; Size = Bank size; GDP = GDP growth rate; GR = Generalized residuals

Variable	N	Mean	SD	Q25	Median	Q75	Min	Max	Skewness	Kurtosis
EVA	1437	-0.427	3.550	-0.038	0.042	0.170	-8.388	89.956	-52.717	5.122
NOPAT	1584	2.158	7.275	0.068	0.308	1.134	6.683	53.710	-0.036	81.473
CACH	1437	2.800	10.631	0.056	0.310	1.281	7.242	63.002	0.000	134.191
D_{AI}	1584	0.316	0.465	0.000	0.000	1.000	0.790	1.624	0.000	1.000
NPL	1584	0.025	0.032	0.008	0.016	0.031	3.503	21.346	0.000	0.336
LDR	1584	0.923	1.353	0.717	0.828	0.948	17.962	351.228	0.230	31.125
MRI	1584	0.253	0.210	0.142	0.224	0.320	6.526	78.796	0.000	3.380
PE	1584	0.833	0.054	0.809	0.841	0.864	-3.255	41.013	0.007	0.983
CE	1584	0.994	0.000	0.993	0.993	0.994	0.123	7.389	0.993	0.994

LEV	1584	11.463	3.994	8.927	11.590	13.820	1.032	11.088	1.595	51.224
Size	1584	10.130	2.015	8.618	10.219	11.464	0.024	2.756	4.964	15.446
GDP	1584	0.039	0.036	0.023	0.047	0.067	-3.774	46.058	-0.540	0.083

Table 3 presents the correlation coefficients matrix. The correlation coefficients of all pairs fall into [-0.7;0.7]. Therefore, collinearity is not a concern.

Table 3. *Pearson correlation coefficient matrix*

EVA = Economic value added; NOPAT = Net profits after tax; CACH = Capital charges; D_{AI} = AI adoption; NPL = Credit risks; LDR = Liquidity; MRI = Market risks; PE = Profit efficiency; CE = Cost efficiency; LEV = Financial leverage; Size = Bank size; GDP = GDP growth rate; GR = Generalized residuals. *p<0.1. **p<0.05.***p<0.01

	D_{AI}	NPL	LDR	MRI	PE	CE	LEV	Size	GDP
D_{AI}	1.0000								
NPL	-0.1629***	1.0000							
LDR	-0.0002	-0.0478*	1.0000						
MRI	-0.0301	0.0225	-0.1014***	1.0000					
PE	0.0294	0.0071	0.0013	0.0201	1.0000				
CE	0.0340	0.0048	-0.0497**	0.0130	0.2356***	1.0000			
LEV	-0.0230	-0.0067	-0.0110	0.0559**	-0.0577**	-0.1931***	1.0000		
Size	0.3915***	-0.3720***	-0.0755***	0.0853***	0.0747***	-0.0272	0.2436***	1.0000	
GDP	-0.2539***	0.0790***	-0.0308	0.0940***	0.0047	-0.1971***	0.1188***	-0.1082***	1.0000

4.2. Baseline results

We present regression results in Table 4. The coefficient of GR is significant in all columns, suggesting that there are omitted factors driving SVA. This justifies our choice of the control function approach.

Column 1 in Table 4 shows a significantly positive coefficient of D_{AI} on EVA at a 1% level, whereas its coefficients are significantly positive in columns (2) & (3) at a 1% level. In terms of economic significance, a one-standard-deviation increase in D_{AI} reduces EVA by 0.046 and increases NOPAT and CACH by 0.030 and 0.032, respectively. Therefore, after adopting AI, commercial banks achieve higher profits. However, their private shareholders also charge higher costs of capital and the amount of capital charges exceeds the increases in profits. Consequently, AI adoption fails to add economic value for bank shareholders. These results are in with shareholder value theory (Fiordelisi & Molyneux, 2006). In sum, our data analysis supports H2.

The signs of control variables are reasonable and in line with prior findings. First, we found bank liquidity and financial leverage increase EVA, which is consistent with studies in EU and Japanese banking (Fiordelisi & Molyneux, 2006, 2010; Radić, 2015). Moreover, we found larger banks are more unable to increase shareholder values, which may be associated with stricter regulations.

Table 4. *Regression results*

The dependent variables are listed at the top of the columns. Standard errors are clustered at the bank level and presented in parentheses. *p<0.1. **p<0.05.***p<0.01. EVA = Economic value added; NOPAT = Net profits after tax; CACH = Capital charges; D_{AI} = AI adoption; NPL = Credit risks; LDR = Liquidity; MRI = Market risks; PE = Profit efficiency; CE = Cost efficiency; LEV = Financial leverage; Size = Bank size; GDP = GDP growth rate; GR = Generalized residuals

	EVA	NOPAT	CACH
	(1)	(2)	(3)
D_{AI}	-0.3545**	0.4695***	0.7238***
	(0.1423)	(0.1385)	(0.2645)
NPL	0.9837	-0.9081	-2.7581
	(1.1471)	(1.5040)	(2.2907)
LDR	1.2671***	0.0110	-0.7523
	(0.3335)	(0.0256)	(0.5160)
MRI	-0.0371	-0.0687	0.5052
	(0.2286)	(0.2335)	(0.4106)
PE	-1.9254	2.3189	5.2568*
	(1.4847)	(2.0504)	(2.8742)
CE	4292.7300	-3637.2970	-18932.7400*
	(3797.0370)	(9023.1160)	(11256.8000)
LEV	0.1295***	-0.0680***	-0.3100***
	(0.0440)	(0.0245)	(0.0804)
Size	-0.5728***	1.5086***	2.2987***
	(0.2025)	(0.3072)	(0.5493)
GDP	-1.3800	0.0089	2.9064
	(1.8515)	(1.0918)	(2.7786)
GR	1.0719***	-0.6512***	-1.7534***
	(0.3639)	(0.2374)	(0.5977)
Observations	1437	1584	1437
R-squared	0.1497	0.2728	0.2595
Year FE	✓	✓	✓
Listing dummy	✓	✓	✓

4.3. Robustness checks

4.3.1. Alternative estimation for the cost of capital

We compare the shadow price of equity with the cost of capital estimated by the capital pricing model for listed banks in Asia-Pacific (Radić, 2015). In order to estimate this standard measure of the cost of capital, we use beta from the Capital IQ database and 10-year US bond interest rates for the risk-free rate. For market risk premium, we followed Fu et al. (2014b) to adjust the bias during the crisis. Fig. 2 shows that our findings are fairly consistent with the traditional cost of capital estimates. Both methods have the same time trend pattern. The shadow cost of equity approach yields approximately 6.06 higher rates than the capital pricing model.

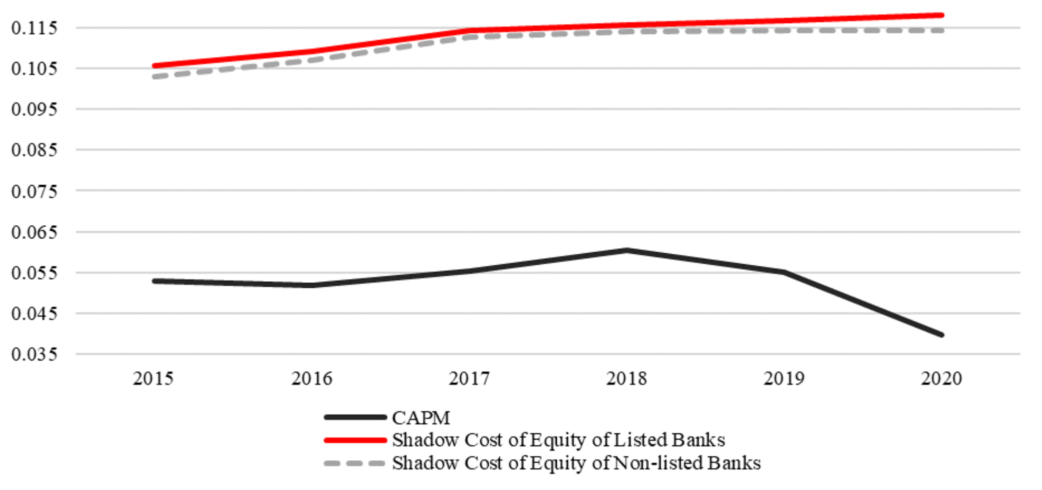

Figure 2. Comparing the cost of capital estimates between two approaches

4.3.2. Alternative estimation method for addressing endogeneity

We checked the sensitivity of baseline results to the choice of estimation method to address potential endogeneity. As such, we re-estimated the baseline model using two-stage least-squares estimators (He et al., 2020; Wooldridge, 2010). In the first stage, we estimated Eq. (2) and then computed the fitted probability of D_{AI}, which is encoded as $\widehat{DAI}$. In the second stage, we replaced D_{AI} with $\widehat{DAI}$ as follows.

$$\mathrm{EVA_{it}} = \alpha_0 + \alpha_1 \widehat{\mathrm{DAI}}_{\mathrm{it}} + \beta_1 \mathrm{X_{1,it}} + \beta_2 \mathrm{X_{2,jt}} + \gamma \mathrm{GR_{it}} + \mu_t + \mu_i + \varepsilon_{it}$$

Panel A in Table 5 shows the consistent results with baseline results, suggesting that the choice of the alternative estimation method is not a concern.

4.3.3. Long-term effects

AI adoption may gradually influence shareholder value creation, which manifests divergent impacts in the short and long run. Prior studies in the literature show that IT adoption has a long-run effect (He et al., 2020; Hernando & Nieto, 2007). To check whether such dynamics drive the results, we estimate the following empirical model that captures both short and long-run:

$$EVA_{it} = \alpha_0 + \alpha_1 D_{AI,it} + \alpha_2\left(D_{AI,i,t-1} + D_{AI,i,t-2}\right) + \alpha_3\left(D_{AI,i,t-3} + D_{AI,i,t-4}\right) + \alpha_4 D_{AI,i,t-5+} + \beta_1 X_{1,it} + \beta_2 X_{2,jt} + \gamma GR_{it} + \mu_t + \mu_i + \varepsilon_{it} \quad (7)$$

The variables $D_{AI,i,t-k}$ (k=1,2,3,4) take the value of one for the k-th year after the adoption of AI and zero otherwise. The variable $D_{AI,i,t-5+}$ takes the value of one for the fifth year and onwards after the adoption of AI and zero otherwise. The coefficient α_1 characterizes the effects of AI adoption in the year of adoption. In this sense, the sum $(\alpha_1+\alpha_2)$ and $(\alpha_1+\alpha_3)$ characterize the effects of AI adoption on shareholder value creation during the first and second, and third and fourth years after the adoption, respectively. The sum $(\alpha_1+\alpha_4)$ characterizes the long-run effects of AI adoption on shareholder value creation during the fifth and onwards after the adoption. Let θ_k be as $(\alpha_1+\alpha_k)$ (k=2,3,4) and . We rewrite the dynamic model (7) as follows:

$$D^*_{AI,it} = D_{AI,it} - \sum_{k=1}^{4} D_{AI,i,t-k} - D_{AIi,t-5+}$$

$$EVA_{it} = \alpha_0 + \alpha_1 D^*_{AI,it} + \theta_2\left(D_{AI,i,t-1} + D_{AI,i,t-2}\right) + \theta_3\left(D_{AI,i,t-3} + D_{AI,i,t-4}\right) + \theta_4 D_{AI,i,t-5+} + \beta_1 X_{1,it} + \beta_2 X_{2,jt} + \gamma GR_{it} + \mu_t + \mu_i + \varepsilon_{it} \quad (8)$$

Panel B in Table 5 shows that the impacts of AI adoption on EVA, NOPAT, and CACH last until 4 years after the adoption. Altogether, they are consistent with the baseline model.

4.3.4. Sample selection bias

Our sampling may also introduce bias. To check the substantiality of this bias in driving the baseline results, we followed He et al. (2020) to estimate Eq. (5) with banks staying in the sample for at least 3, 4, and 5 years. Panel C from Table 5 suggests a consistent finding.

Table 5. *Robustness checks*

The dependent variables are listed at the top of the columns. Standard errors are clustered at the bank level and presented in parentheses. *p<0.1. **p<0.05.***p<0.01. EVA = Economic value added; NOPAT = Net profits after tax; CACH = Capital charges; D_{AI} = AI adoption.

	EVA (1)	NOPAT (2)	CACH (3)
Panel A: Two-stage least-squares estimation			
$\widehat{DAI}$	-0.6640** (0.2718)	1.1997*** (0.2026)	1.4889*** (0.3429)
Panel B: Long-term effects			
AI adoption	-0.3125** (0.1542)	0.4367*** (0.1552)	0.6710** (0.2909)
AI adoption (1st and 2nd years)	-0.4101*** (0.1445)	0.4815*** (0.1318)	0.8136*** (0.2386)
AI adoption (3rd and 4th years)	-1.2860* (0.6932)	1.0822** (0.4306)	2.2398** (1.0871)
AI adoption (5th year and onwards)	-1.4848 (1.4808)	-0.6069 (0.7031)	0.4686 (1.1143)
Panel C: Sample selection			
D_{AI} (staying at least 3 years)	-0.3476** (0.1431)	0.4631*** (0.1385)	0.7177*** (0.2652)
D_{AI} (staying at least 4 years)	-0.3795** (0.1502)	0.4744*** (0.1443)	0.7681*** (0.2779)

D_{AI} (staying at least 5 years)	-0.3754**	0.4631***	0.7573***
	(0.1519)	(0.1444)	(0.2812)
D_{AI} (staying full 6 years)	-0.3952**	0.4886***	0.7615**
	(0.1669)	(0.1578)	(0.3093)
Control variables	✓	✓	✓
Year FE	✓	✓	✓
Listing dummy	✓	✓	✓

5. Further Analysis

It is important to investigate whether the impacts of AI adoption on shareholder value are affected by various sources. From a policy perspective, it allows stakeholders to understand to what extent AI adoption destroyed shareholder value, thus proposing appropriate strategies to cope with. We used the following model estimation (He et al., 2020):

$$EVA_{it} = \alpha_0 + \alpha_1 DAI_{it} + \alpha_2 DAI_{it} \times SOURCE_{it} + \beta$$

5.1. Size

We set $SOURCE_{it}$=$Large_{it}$, a binary variable equal to 1 for medium and large banks, and 0 otherwise, to check how AI adoption affects shareholder value depending on bank size. Banks are heterogeneous in size, therefore different-sized banks may have different strategies to use AI. In this study, we arbitrarily defined medium and large (small) banks as those whose total assets in 2020 are greater than or equal to (less than) USD 50000 million. Digital Banking Report research showed that 48% of financial institutions whose total assets are over USD 50000 million have deployed at least one AI solution, and this number descends for lower asset classes (Jim, 2017). Panel A of Table 6 shows that at a 1% significance level, larger banks enjoy 0.500 higher operating profits than smaller banks thanks to AI adoption. However, at a 10% significance level, private shareholders charge 0.511 higher cost of capital for larger banks. Consequently, there is no difference between large and small banks after adopting AI in terms of shareholder value creation.

5.2. COVID-19

It is of interest to consider the impacts of the COVID-19 pandemic on the impacts of AI adoption. Due to defense mechanisms and social distancing, customers are more induced to shift toward the digital landscape for financial services rather than physical branches. We used two measures to cover the pandemic effects. The first dummy presents the timeline of the COVID-19 crisis, coded as D_{COVID}, which is equal to 1 for the year 2020 (when the pandemic globally spreads) and 0 otherwise. The second measure advances the first measure by considering the COVID-19 travel health notice level following The Centers for Disease Control and Prevention (CDC) categories. The dummy $D_{Severity}$ takes values from 1 to 4 according to the low to very high severity[2]. Panel B of Table 6 shows that during the time of the COVID-19 crisis, there is no difference found in terms of profits, capital charges, and shareholder value creation. However, when considering the pandemic severity, the analysis shows that banks in

[2] CDC defined an incidence rate as new cases over the past 28 days per 100,000 population. Based on incidence rate, they catergorize the COVID-19 travel health notice level into 4: low (few than 50), moderate (50-99), high (100-500), and very high (more than 500).

high-severity countries suffer a loss of 0.194, but their private shareholders charge a 0.370 less amount of capital costs. Therefore, shareholder wealth creation is 0.179 higher.

Table 6. *Additional analysis*

The dependent variables are listed at the top of the columns. Standard errors are clustered at the bank level and presented in parentheses. *p<0.1. **p<0.05.***p<0.01. EVA = Economic value added; NOPAT = Net profits after tax; CACH = Capital charges; D_{AI} = AI adoption; D_{Large} = Large banks; D_{COVID} = 2020 year (when the COVID-19 pandemic occurs); $D_{Severity}$ = Country severity level of the pandemic.

	EVA	NOPAT	CACH
	(1)	(2)	(3)
Panel A: Size			
D_{AI}	-0.2745**	0.1625	0.4061
	(0.1357)	(0.1249)	(0.2533)
$D_{AI}\times D_{Large}$	-0.1291	0.5003***	0.5111*
	(0.1595)	(0.1371)	(0.2792)
Panel B: COVID-19 Pandemic			
Part I: Timeline			
D_{AI}	-0.3386**	0.4663***	0.7054**
	(0.1572)	(0.1426)	(0.2828)
$D_{AI}\times D_{COVID}$	-0.0628	0.0114	0.0725
	(0.1602)	(0.1130)	(0.2288)
Part II: Severity level			
D_{AI}	-0.4139**	0.5373***	0.8434***
	(0.1634)	(0.1518)	(0.2945)
$D_{AI}\times D_{COVID}\times D_{Severity}$	0.1794*	-0.1937***	-0.3697***
	(0.1010)	(0.0632)	(0.1359)
Control variables	✓	✓	✓
Year FE	✓	✓	✓
Listing dummy	✓	✓	✓
Control function	✓	✓	✓

6. Conclusion

This study aims to respond to whether AI usage assists commercial banks in creating economic value for their shareholders. Utilizing an unbalanced panel of 302 commercial banks in 19 economies across Asia-Pacific from 2015 to 2020, the study finds that although increases in operating profits, AI use fails to increase shareholder wealth due to higher capital charges. This adverse effect lasts at least four years after the adoption. Moreover, the study shows that larger banks can escape from the negative effects of AI adoption on shareholder value, and shareholders are more reluctant to charge higher capital costs given the higher severity of the pandemic.

Our study poses several theoretical implications. First, this study contributes to the sparse literature on shareholder value in Asia-Pacific by showing that AI use is an additional determinant of shareholder value besides bank size, financial leverage, efficiency, and risk exposures. Second, this study advances the well-known “profitability paradox”[3] by showing that even if investing in high-tech applications such as AI increases profits, banks also fail to create economic value. In this study, we found that decreases in EVA link to higher capital charges. Third, aligned with the risk-return trade-off of IT use within the banking context, our study implies banks face a dilemma: returns versus responsibility because the goal of bank management is to enrich shareholder wealth (Fu et al., 2014b).

Similar to any research, we encounter unavoidable limitations. First, during the time conducting the research, very few banks in Asia-Pacific adopted AI for more than 5 years. When the adoption further diffuses, we suggest followers refine our findings. Second, due to limitations in technical aspects (e.g., IT human resources), our findings may be not presentative for US or EU banking. We kindly encourage followers to test our findings in these markets. Third, future studies should consider testing our baseline results with alternative measures (e.g., Tobin’Q, stock-based performance) of shareholder value creation besides EVA.

[3] The profitability paradox claims that IT investment cannot lead to profitability for commercial banks (Beccalli, 2007)

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