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2025 AFTN SEMINAR

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Fintech: Financial Inclusion or Exclusion?

Yoke Wang Tok and Dyna Heng

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Fintech: Financial Inclusion or Exclusion?
Prepared by Yoke Wang Tok and Dyna Heng*

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ABSTRACT: This paper examines the role of Fintech in financial inclusion. Using Global Findex data and emerging fintech indicators, we find that Fintech has a higher positive correlation with digital financial inclusion than traditional measures of financial inclusion. In the second stage of our empirical investigation, we examine the key factors that are correlated with the Fletcher School's three digital divide – gender divide, class (rich-poor) divide and rural divide. The results indicate that greater use of fintech is significantly associated with a narrowing of the class divide and rural divide but there was no impact on the gender divide. These findings imply that Fintech alone may not be sufficient to close the gender gap in access to financial services. Fintech development may need to be complemented with targeted policy initiatives aimed at addressing the gender gap directly, and at changing attitudes and social norms across demographics.

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WORKING PAPERS

Fintech: Financial Inclusion or Exclusion?

Prepared by Yoke Wang Tok and Dyna Heng

Contents

Glossary

ASEAN	Association of Southeast Asian Nations
DAI	Digital Adoption Index
DII	Digital Intelligence Index
EAP	East Asia and Pacific
IMF	International Monetary Fund
LAC	Latin America and Caribbean
MEA	Middle East and North Africa
OECD	The Organization for Economic Co-operation and Development
SSA	Sub-Saharan Africa
WB	The World Bank

Executive Summary

This paper examines the role of Fintech in financial inclusion. Using Global Findex data and emerging fintech indicators, we find that Fintech has a higher positive correlation with digital financial inclusion than traditional measures of financial inclusion. In the second stage of our empirical investigation, we examine the key factors that are correlated with the Fletcher School's three digital divide – gender divide, class (rich-poor) divide and rural divide. The results indicate that greater use of fintech is significantly associated with a narrowing of the class divide and rural divide but there was no impact on the gender divide. These findings imply that Fintech alone may not be sufficient to close the gender gap in access to financial services. Fintech development may need to be complemented with targeted policy initiatives aimed at addressing the gender gap directly, and at changing attitudes and social norms across demographics.

I. Introduction

Fintech is transforming financial services. By leveraging technology and cloud-based data, financial institutions are offering products better tailored to consumers' needs at a lower cost (Arner et al., 2020; Boot et al., 2020; Philippon, 2020; Thakor, 2020). As a result, many expected that Fintech would promote financial inclusion and benefit disadvantaged groups (Demirguc-Kunt et al., 2018; Breza et al., 2020). However, despite the plethora of papers on this topic, very few have provided direct empirical evidence of the impact of Fintech on financial inclusion. This is due to challenges in measuring Fintech as its products differ greatly in scope and scale, and in measuring the "digital" aspect of financial inclusion. The patchy data and short time series have also compounded the challenge.

This paper examines two research questions. First, does Fintech improve digital financial inclusion? Second, are there segments of society that are not included because they do not have the capacity and means to adopt Fintech – such as women, the poor and people living in rural areas?

Traditional indicators of financial inclusion, such as bank accounts and branches, cannot capture the role of Fintech in digital financial inclusion. To better assess this role, we use new digital financial inclusion indicators and various Fintech proxies in this paper. They are the Digital Financial Inclusion Index (Sahay et al. 2020), the Fletcher School's Digital Intelligence Index (DII), and the World Bank's digital adoption index (DAI).

Based on our panel regression, the paper draws three conclusions. First, Fintech has a positive correlation with financial inclusion, with the largest correlation occurring when digital financial inclusion is used. Second, Fintech has a negative association with the class divide and rich-poor divide (i.e. it has the potential to make it better). Third, Fintech has no impact on the gender digital gap. These findings imply that Fintech alone may not be sufficient to close the gender gap in access to financial services. Fintech development may need to be complemented by targeted policy initiatives aimed at addressing the gender gap directly, and at changing attitudes and social norms across demographic groups.

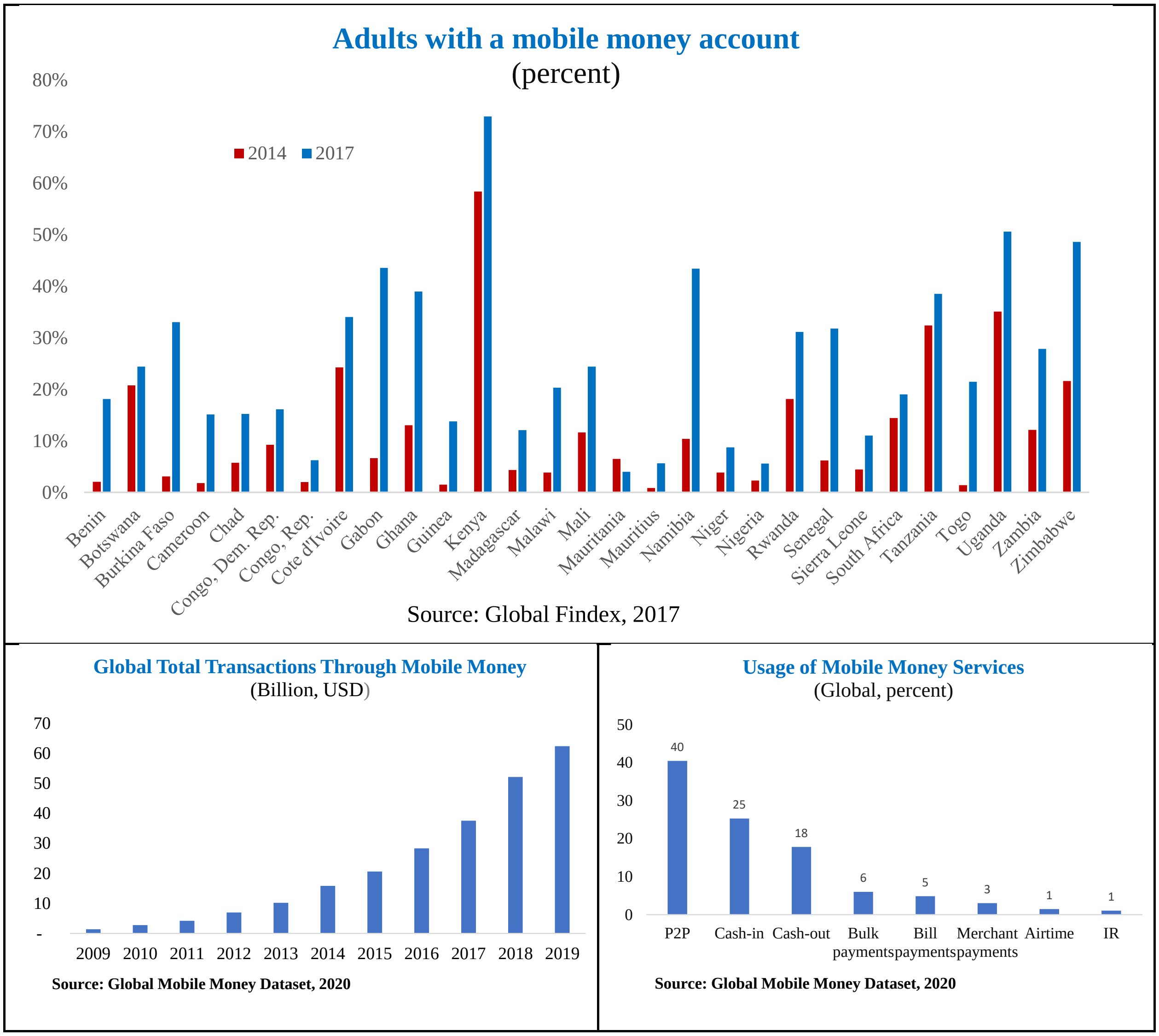
The paper is organized as follows: Section 2 reviews the recent trends and research on the role of Fintech in financial inclusion; Section 3 discusses the gender, rural, and rich-poor gap; Section 4 reviews the traditional and new indices of digital financial inclusion and the methodology used in this paper; Section 5 discusses the empirical analysis; and Section 6 describes the results. Section 7 sets out the conclusions and provides various policy recommendations.

II. RECENT TRENDS AND LITERATURE

Fintech products differ greatly in scope and scale: cross-border payments, peer-to-peer loans, and credit risk assessments. Overall, the areas that Fintech covers can be categorized into: (i) credit, deposits, and capital-raising services; (ii) payments, clearing and settlement services, including digital currencies; (iii) investment management services; and (iv) insurance. Fintech is growing rapidly and at varying speeds across regions and countries. For instance, there has been a significant increase in the number of mobile accounts and usage of mobile money services (Figure 1).

Digital financial inclusion refers to the digital access and usage of formal financial services through mobile phones and computers. These include digital payments, digital lending/credit, marketplace lending, mobile money, and mobile banking (Sahay et al. 2020). In many countries, digital financial inclusion increased between 2014 and 2017, even where traditional financial inclusion was stalling or declining (World Bank 2018). Fintech is expected to fill gaps in both payments and lending, especially where the traditional delivery of financial services is less available. Demirg¨u¸c-Kunt et al. (2017) provided a comprehensive survey on financial inclusion. Fuster et al. (2019) and Tang (2019) showed that Fintech often serves as a complement to, rather than a substitute for, traditional banking services. On the contrary, Hau et al. (2018), Jagtiani and Lemieux (2018), Sumit et al. (2019), and Frost et al. (2019) argued that Fintech and big tech lenders serve borrowers who are traditionally underserved by banks.

Figure 1: The rise of mobile money accounts and services



Despite the rapid growth of Fintech, studies of its impact on financial inclusion have been limited. Studies of how Fintech has narrowed the digital gaps across gender, income and rural areas are even scarcer. This is largely due to the lack of comprehensive data on Fintech variables and digital financial inclusion indicators. The traditional financial inclusion indicators fall short of capturing digital financial inclusion, and analysis of the effect of Fintech on financial inclusion could lead to wrong conclusions if we are unable to measure financial inclusion properly.

Fintech can have negative correlations with the traditional measures of access and usage, such as the number of ATMs, bank branches and bank account per capita. For example, Tashin et al. (2018) found that leapfrogging (mobile phone over fixed lines) has negative correlations with the number of deposits and loans per capita in many countries. However, in the Pacific Islands, Tashin et al. (2018) found leapfrogging to be complementary to traditional banking services. In the Solomon Islands, mobile banking has complemented traditional banking in the areas of remittances.

Sahay et al. (2020) went beyond the anecdotal evidence to provide empirical support that Fintech promotes financial inclusion. Fintech solutions such as mobile money, mobile-point-of-sale devices and crowdfunding have provided low-cost, efficient, and collateral-less avenues for households and firms to pay, obtain credit, and support their cash management. They constructed a new indicator of digital financial inclusion using digital payment services data provided through mobile phones and the internet, and another traditional financial inclusion index for financial services provided by traditional financial institutions. Their new measure suggests that digital financial inclusion increased significantly in the years preceding the COVID-19 crisis, particularly in Africa. In eight countries, including Zimbabwe (where mobile payments have replaced cash transactions), South Africa and Nigeria, the improvement in financial inclusion has been entirely driven by Fintech. They also showed that Fintech has contributed to closing gender gaps in financial inclusion. In other words, digital financial inclusion gender gaps are lower on average than the traditional financial inclusion gender gaps. This is true overall and specifically for countries in Africa, the Middle East and Central Asia. However, for countries in Asia-Pacific, Latin America and the Caribbean, digital financial inclusion gender gaps are actually higher than the traditional financial inclusion gender gaps, demonstrating that the more Fintech is used the greater the gender divide.

On the contrary, Chen et al. (2021) used an individual-level survey dataset for 28 countries and found a persistent "Fintech gender gap" that could pose an obstacle to financial inclusion. They also found that the gender gap was smaller among products that complement traditional banking services relative to those that are substitutes. Women are more likely to adopt Fintech products that complement familiar services. This suggests that the gap in the use of Fintech is closely linked to differences in attitudes towards technology and price sensitivity. In their survey, more women than men said that they worry about their security when dealing with companies online. Women also reported being significantly less willing to adopt new financial technology, for example digital banks, and less willing to use a Fintech product even if it what it offers is superior or better suited to the respondent's lifestyle.

Similarly, Cheah et al. (2021) look at the gender divide in the ASEAN payment system (both traditional and digital) and find that gender gap persists in digital models like mobile money. Their results show that women are more likely to use traditional payment methods like cash and that age exacerbates the gender divide in the usage of financial institutions for payment.

The literature is evolving as the evidence remains scarce and sometimes contradictory. This paper looks at the issue from a different angle – that of exclusion instead of inclusion. Exclusion is the flipside of inclusion, for instance, if the percent of population making digital payments is 60%, this means that 40% do not use digital payments. By doing so, we alert policymakers to the segments of society that have been left behind by the push for digitalization. Not all gaps need to be closed because there will always be voluntary exclusion, and not all firms and households need financial services (e.g., farmers in Thailand). It is not the policy objective to close all gaps because there may be structural reasons why a gap exists, and there are risks and costs involved in closing those gaps.

The Dark Side of Fintech

Fintech has been touted as a force for good. The business models of Fintech startups are geared towards solving real-life problems such as payment apps that make it almost free and painless for migrant workers to send money home to the most remote villages. These payments and FinTech lending services are seen to fill a gap where traditional delivery of financial services is lacking; for example, crowdfunded lending to SMEs fills a financing gap and improves cash flows (Tok, Tan and Chansriniyom. (2020)). However, as digital financial services become more ubiquitous and gain greater traction, researchers and regulators are becoming m ore aware of the "dark side of Fintech" and the need to address it urgently.

What do we mean by the "dark side" of Fintech? It is about the exclusion of certain groups in society: women, the aged, the poor and minority groups. The "dark side" also refers to algorithm biases and predatory lending practices that have a negative impact on vulnerable groups. As the pandemic accelerated the switch towards digital financial services there is a risk that the "dark side" has grown even bigger. For example, those without access to digital payments or deposit accounts are excluded from government support that is delivered via government-to-person (G2P) payments. Even in the US, where financial inclusion is high – 93% of adults have a bank account – there exists a 13 percent point gap between the wealthiest households and the poorest. Financial exclusion could arise from various sources, including the lack of access to digital infrastructure such as mobile phones, computers or the internet, financial and digital illiteracy, potential biases in algorithms, and/or lack of trust. The following paragraphs highlight the areas where financial exclusion might arise. However, our focus in this paper is on the Fintech gender, rural and class divide as this was dictated by the data available.

Fintech gender gap: Women in general have lower rates of bank account ownership than men (Demirguc-Kunt et al., 2017), are less likely to manage household finances (Guiso and Zaccaria, 2021) or to participate in the stock market (Ke, 2020). Sahay et al. (2020) found that while Fintech has contributed to closing gender gaps in financial inclusion in most countries, there is a concern that this gender gap might widen in the post-COVID era. This finding is supported by interviews with stakeholders who pointed out that Fintech does not address barriers such as cultural or social norms, financial and digital literacy, and safety and disparity in access to resources, and that such barriers are higher for wom en.

A recent paper by the BIS[1] found that 29% of men use Fintech products and services as compared to 21% of women.[2] The Fintech gender gap (8 percent point) was larger than the gap in bank account ownership between

[1] BIS Working Paper No. 931.

2 The paper used micro-level survey data from the 2019 Ernst and Young Global Fintech Adoption Index. The survey covers over 27,000 adults from 28 major economies.

men and women[3] (7 percent point)[4], and existed in all countries. The authors found that the gap could not totally be explained by either country-specific circumstances or individual characteristics such as age, education, income, and marital and employment status. Their results suggest that the gap in Fintech use is due to differences in attitudes and preferences towards new financial technology between genders. Women are more risk averse than men and are less willing to adopt new financial technology, irrespective of whether it is offered by new players or incumbents. The authors postulated that the gender gap could narrow as these new Fintech products become more standardized and regulated over time. This difference in attitudes between men and women could reflect social norms. For example, women worry more about privacy and personal data protection than men. It could also reflect gender-based discrimination, such as previous bad experiences with financial institutions (Bartlett et al, 2019). In addition, the fintech gender gap could be traced to the lack of access to the internet. According to the Alliance for affordable internet (2021), only 48% of women has access to the internet compared to 55% for men globally. The answer could also lie in the design of Fintech applications that are too male-centric and do not cater to women. Further research is needed in this area.

The following paragraphs highlight two other aspects of financial exclusion that are important but not covered in this paper.

Aging and financial exclusion: The G20 Fukuoka Policy Priorities on Aging and Financial Inclusion (2019)[5] noted ten factors that could contribute to financial exclusion of elderly people. They are: low digital capability; low financial literacy; cognitive decline; physical decline; social isolation; living on a fixed income, pension or annuity; reliance on family members; difficulty accessing financial advice; lack of financial products for older persons; and reliance on financial professionals. This is an important area that deserves more research. As many developed and developing economies are aging rapidly, technology could be leveraged to help the aged and understand the factors that drive financial exclusion for this segment of the population. It would also help in the design of products and policies to address this gap.

Biases in algorithmic scoring: Several papers have raised the issue of fairness and accuracy in data and algorithmic credit scoring that lead to biases against lower income and minority groups as well as women. Algorithms used by banks to predict credit card debt defaults typically favor wealthier white applicants (Heaven 2021). This is primarily due to the noise in the data that led to inaccurate predictions. A fairer algorithm would not fix the problem. In another study of mortgage data, Laura and Blattner ((2021) similarly concluded that differences in mortgage approvals between minority and majority groups were not attributed only to bias but to the fact that minority and low-income groups have less data, which in turn leads to less precise predictions. It is this lack of precision and not just bias that leads to inequality. In addition, even a gender-blind algorithm could end up biased against women as long as it draws on any input that happens to correlate with gender (Abuhamad, 2020). Similarly, Gilis (2021) showed that discrimination is already inherent in the data and excluding protected characteristics such as race did not solve the problem. As such, she advocated that fair lending laws should shift to an outcome-focused, welfare-oriented approach.

[3] IMF (2020), The Promise of Fintech: Financial Inclusion in the Post Covid-19 Era.
[4] Demirguc-Kunt et al. (2018).
[5] The report was prepared by Global Partnership for Financial Inclusion (GPFI) and OECD, 2019.

III. Mind The Gap

Using data from World Bank's Findex survey (2017), we illustrate the gender gap as the white space between the female (red bar) and the male (blue bar) below. The most striking message from the charts is that the gender gap exists across all regions. This fact is well-documented in the literature (BIS 2021, IMF 2020b). The gap is persistently largest across the three measures (accounts, used internet to pay bills, and made or received digital payments) and across the Middle East and North Africa (MEA), Sub-Saharan Africa (SSA), and South Asia. For instance, in MEA the gender gap as measured by the number of accounts is 19 percent points (Figure 2). In general, the gender gap narrows when we move from the accounts measure of inclusion to the two digital measures. **The average gender gap across all regions, using the accounts measure, is 11 percent points.**

Figure 2: Number of Accounts

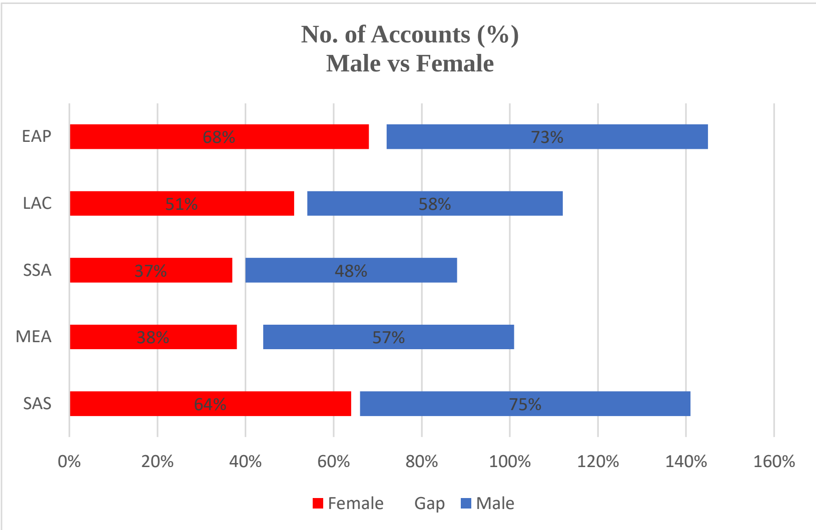


Figure 3: Used Internet to Pay Bills

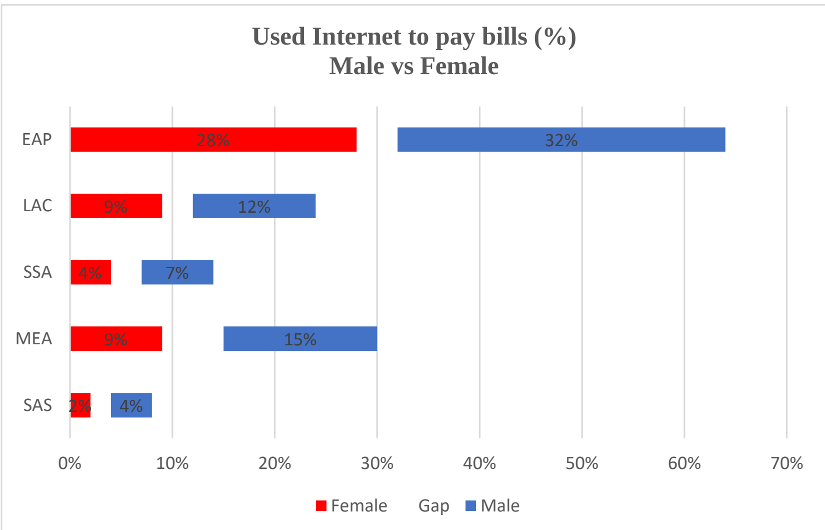
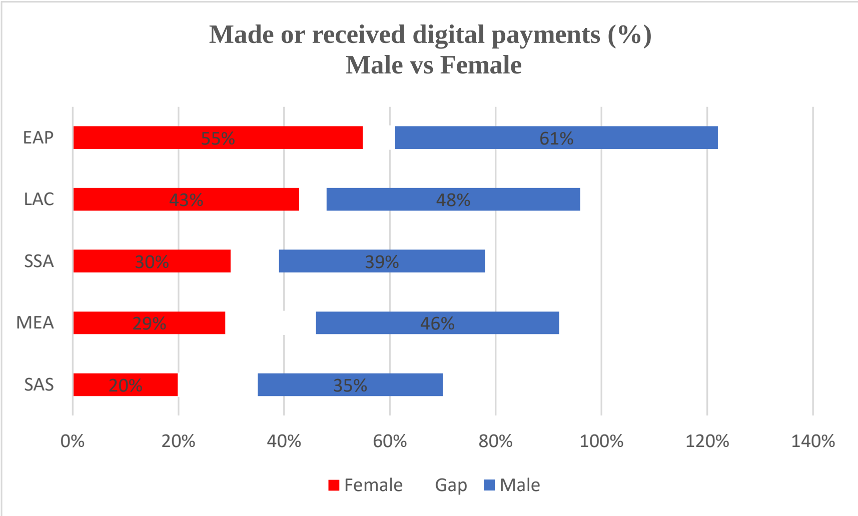


Figure 4: Digital Payments



The average rich-poor gap is 15 percent points across all regions. The gap between the rich and poor is most pronounced in Latin America and Caribbean (LAC, 21 percent points) and East Asia and Pacific (EAP, 19 percent points) using the accounts measure. They did not narrow when the digital measures were used (Figures 3 and 4). By contrast, the rich-poor gap is smaller in SSA, MEA and SAS, and even smaller when digital measures are used (Figures 5 to 7).

Figure 5: Number of Accounts

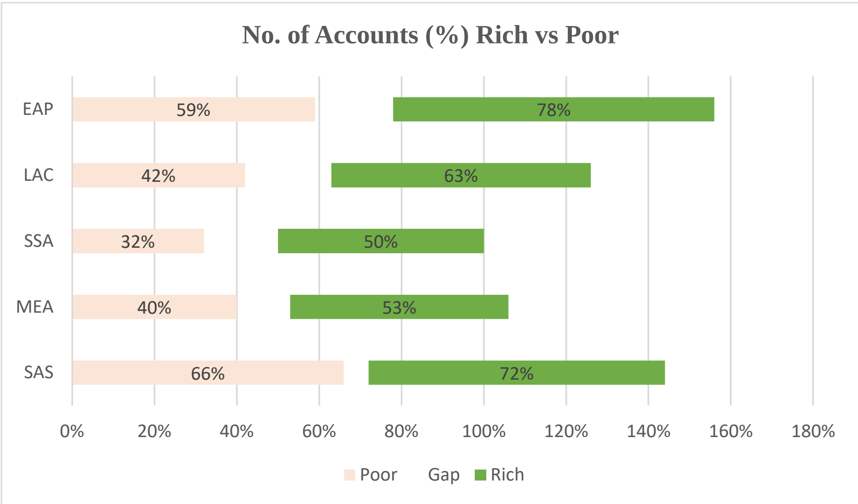


Figure 6: Internet Usage

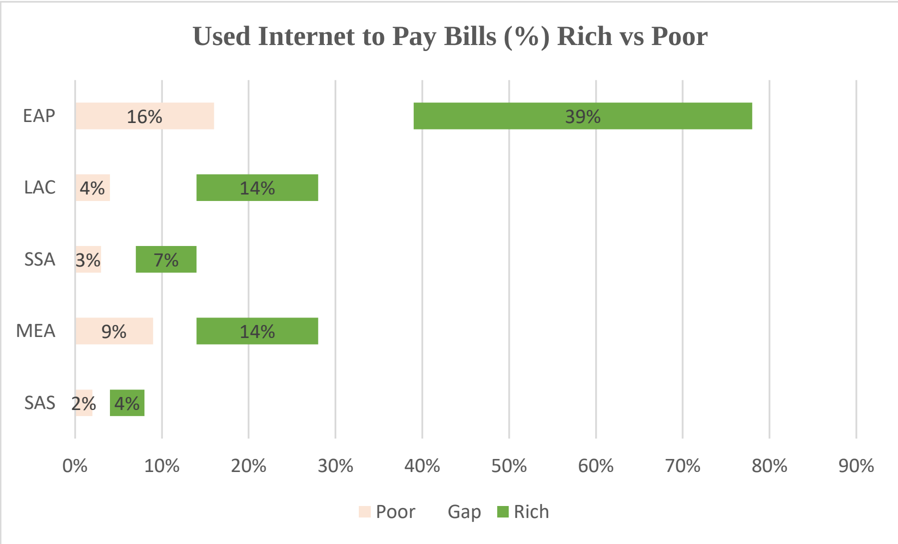
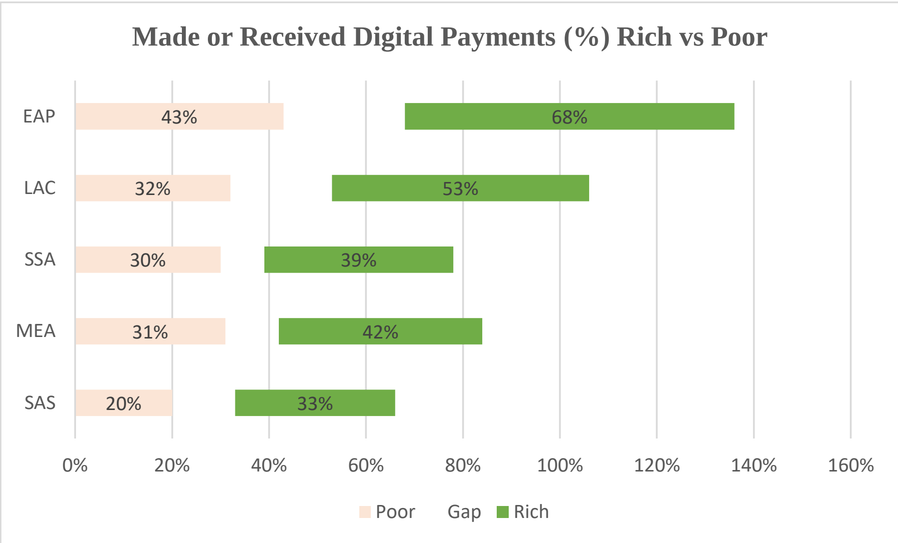


Figure 7: Digital Payment



IV. Data and Empirical Approach

In this paper we use three digital financial inclusion indicators, two traditional financial inclusion indicators, and four Fintech proxies. They are described in Table 1 below. The three digital financial indicators were chosen because to our knowledge they are the only ones available and to which we have access. The four Fintech proxies are: (1) leapfrog; (2) venture capital raised for Fintech businesses; (3) business volume raised from crowdfunding platforms; and (4) mobile money accounts. Table 1 below lists the variables used in this study. More details about definitions and sources may be found in Appendix A.

Table 1: Summary of Indicators Used in Regression

Fintech Proxies	**Digital Financial Inclusion Indicators**	**Traditional Financial Inclusion Indicators**	**Measures of Digital Divide**
Leapfrog (proxied by mobile phones/fixed line subscriptions)	Digital Financial Inclusion Index	Traditional Financial Inclusion Index	Gender divide: the deviation of female digital usage from male. The higher the number, the better, i.e., less divide.
Venture capital raised for Fintech companies (as % of GDP)	Digital Intelligence Index (DII)	Number of bank branches	Rural divide: the deviation of rural digital usage from the average. The higher the number, the better.
Total amount of funds raised through P2P lending platforms (as % of GDP)	Digital Adoption Index (DAI)		Class divide: the deviation of the bottom 40% from the top 60%.
Mobile money accounts			

Review of Digital Financial Inclusion Indicators

In this paper, we focus on the following three digital financial inclusion indices:

Digital Financial Inclusion Index (Sahay et al. 2020)**:** Based on the principal component analysis, the index aggregates digital payment services through mobile phone and internet usage**.** The index covers 52 EMDEs for 2014 and 2017. Sahay et al. 2020 also constructed “traditional” financial inclusion index for financial services provided by traditional financial institutions.. With these two indices, a comprehensive financial inclusion index was constructed using a three-stage principal component analysis. The first stage combined various indicators to compute measures of “access” to and “usage” of payment services separately for both traditional and digital financial inclusion. The second stage computed “traditional financial inclusion” and “digital financial inclusion” indices combining the respective access and usage indicators from the first stage. The third and final stage combined traditional and digital financial inclusion indices to build a comprehensive financial inclusion index of a country.

Fletcher School's Digital Intelligence Index (DII) [6]**:** This index takes a comprehensive approach to measure the digitalization of an economy within a framework. Digitalization is driven by four key drivers of equal importance: supply conditions, demand conditions, institutional environment, and innovation and change. It covers 90 economies from 2008 to 2019 and uses a total of 160 indicators. (For more details see the methodology in Appendix B.)

World Bank's Digital Adoption Index (DAI) is a composite index that measures the depth and breadth of the adoption of digital technologies in 171 countries. It uses 16 indicators of sectoral sub-indices covering businesses, people and governments, with each sub-index assigned an equal weight. It covers the period from 2014 to 2016. It is meant to provide a comprehensive picture of technology diffusion in an economy and not just in the financial services sector. As a result, it is a broader measure than the other two indices used in this study. The DAI was constructed using data on coverage and usage, often from the World Bank's internal databases, and therefore is likely to be more robust than those based on perception surveys.

The correlation between these three indices and their descriptive statistics is as follows:

Table 2: Correlation Matrix

	No. of accounts	Branches	Traditional Financial Inclusion	Digital Financial Inclusion Index	Digital Intelligence Index	World Bank Digital Adoption Index
No. of accounts	X	0.56	0.89	0.35	0.87	0.86
Branches		X	0.67	-0.04	0.38	0.50
Traditional Financial Inclusion Index			X	0.22	0.76	0.82
Digital Financial Inclusion Index				X	0.33	0.42
Digital Intelligence Index					X	0.88
World Bank Digital Adoption Index						X

[6] https://digitalintelligence.fletcher.tufts.edu/methodology

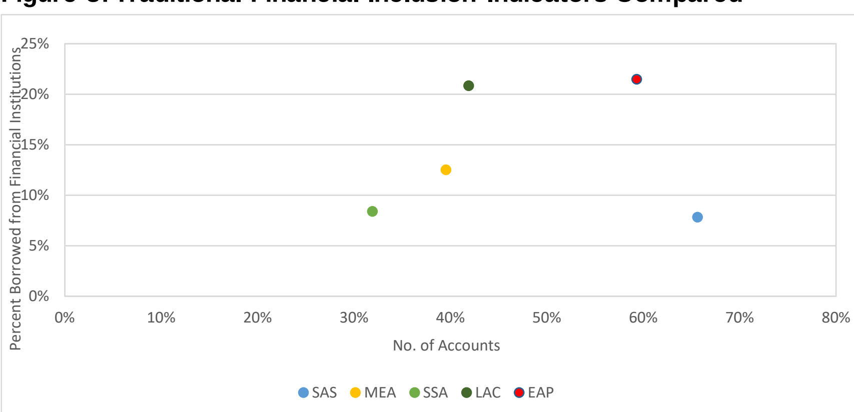
	Traditional Financial Inclusion Index	Digital Financial Inclusion Index	Digital Intelligence Index	WB Digital Adoption Index
Mean	0.33	0.36	0.51	0.5
Standard deviation	0.22	0.20	0.19	0.19
Min-Max	0.0-1.0	0.0-1.0	0.1-1.0	0.1-0.8

Table 2 shows the correlation among these key indices. The highest correlation is between the Digital Intelligence Index and the World Bank Digital Adoption Index. The lowest correlation (0.2) is to be expected between the IMF traditional Financial Inclusion Index and the IMF-Fintech Driven Index because the two indices were constructed to be distinct. The IMF-Fintech Driven Index has only a 0.3 and 0.4 correlation with the Digital Intelligence Index and the Digital Adoption Index respectively. Notably, the correlations between the number of accounts and the various financial inclusion indicators are positive, while that between the Fintech financial inclusion indicator and branches is negative. This provides preliminary evidence that Fintech is a substitute for bank branches. We provide more evidence below.

Traditional vs Digital Fintech Indicators

Financial inclusion is like a huge elephant – it is multi-faceted. Imagine that you are blind and have never seen an elephant. If you touched its ears you would think that the elephant is soft and flappy, but if you touch its legs you would think that it looks like a tree trunk. Similarly, if you were to look at financial inclusion in terms of the number of accounts, it would look relatively high (Figure 8) at 71% for East Asia-Pacific; however, the borrowing is only 21% each for East Asia and Pacific and Latin American countries, and only 8% each for Sub-Saharan Africa and South Asia. This could lead one to conclude that financial inclusion is a problem in the area of borrowing/lending. Indeed, Fintech innovations such as mobile money and peer-to-peer lending exist to fill this lending gap and have been found to be quite successful (Bazarbash, Majid, Beaton, Kimberly (2020), Tok et al. (2020)). As noted in Sahay et al. (2020), across all regions and income levels borrowing activity is much less widespread than account holding. Even in wealthy countries, an adult is over four times as likely to have an account than to borrow from a formal financial institution (Barajas et al. 2020).

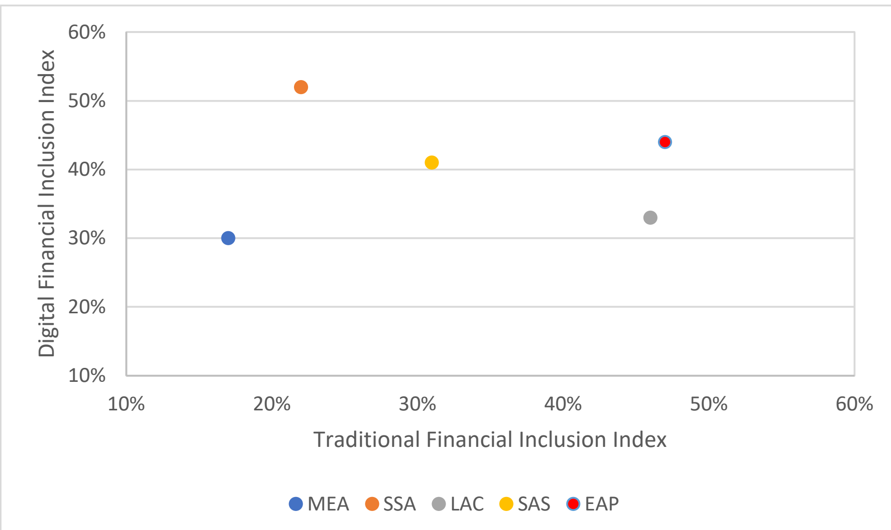
Figure 8: Traditional Financial Inclusion Indicators Compared



Source: World Bank Findex. SAS= South Asia, MEA = Middle East and Africa, SSA = Sub-Saharan Africa, LAC= Latin America and Caribbean, EAP = East Asia and Pacific.

To get a more accurate view of the elephant it is useful to look to at the digital index. In Figure 9, we compare traditional and digital financial inclusion index (Sahay et al. 2020). East Asia and Pacific, and Latin America and Caribbean have higher levels of traditional financial inclusion. However, when it comes to digital financial inclusion, Africa and again East Asia are ahead. Notably, nine African countries (including Ghana, Kenya, Senegal and Uganda) have the highest digital financial inclusion indices, while China is only in tenth position. This illustrates how Africa is at the forefront of leading Fintech innovation (see results on leapfrogging in Section V), primarily through the use of mobile money which has reduced the fixed cost of providing financial services to many people in Africa and has boosted financial inclusion. In other words, if we had measured financial inclusion the traditional way, we would have missed this African leapfrogging story.

Figure 9: Traditional vs Digital Financial Inclusion Index (2017)



V. Empirical Assessment

This section sets out our empirical approach and results. First, in equation (1), we examine and compare the correlation of Fintech on financial inclusion using the indicators reviewed in the previous section. Second, in equation (2), we focus on the three digital divides constructed by the Fletcher School, namely, the gender divide (e.g. percent of women's use of digital payments divided by percent of men's use of digital payments), class divide (e.g. use of digital payments by the poorest 40% divided by the richest 60%) and the rural divide (rural vs population mean). (See Appendix A for definitions.) In our regressions, we have reversed the signs for the divide variables, so that a lower number (i.e. a smaller gap). means an improvement As we would like to examine the correlation between the fintech and the three divides, we control for other "environment factors" such as the regulatory quality, education levels, trust and gender inequality (structural issues facing women across three dimensions – health, empowerment and the labour market).

The analysis uses fixed-effect model with robust standard errors. The specification is as follows:

$$FI_{it} = c + \beta_1 X_{it} + \beta_2 Fintech_{it} + \alpha_i + \varepsilon_{it} \qquad (1)$$

where FI is either digital or traditional financial inclusion as listed in Table 1; 'Xs' are the controls, which include per capita income, credit to private sector, education level, regulatory quality, population, internet penetration, and mobile phone penetration; and Fintech is the respective Fintech proxies listed in Table 1. The choice of the independent variables follows the literature (OECD, 2012; Dabla-Norris et al. 2015;). Education, for instance, has been found to be important in reducing income inequality as it determines occupational choice, access to jobs, and the level of pay, and plays a pivotal role as a signal of ability and productivity in the job market.

A. Does Fintech Promote Financial Inclusion?

First, we ran panel regressions with fixed effects to examine the effect of Fintech on financial inclusion using various traditional and digital financial inclusion measures and different proxies for Fintech. As shown in Table 3, the coefficient of Fintech proxied by leapfrog and capital raised have positive signs and are statistically significant in most regressions with digital financial inclusion and the Digital Intelligence Index (DII). These results suggest that the two Fintech proxies have a positive effect with digital financial inclusion that is consistent with the emerging literature. (See for example, Sahay et al. 2020.) In contrast, leapfrogging has no significant effect with the traditional financial inclusion indicator (i.e., bank branches), and capital raised has no correlation with the traditional financial inclusion indicator (Eq 2, 5, 8). These results imply that using traditional financial inclusion to measure the role of Fintech could lead to the wrong conclusions. As discussed in the previous section, leapfrogging has a negative correlation with traditional indicators and branches (Eq 2), implying that Fintech is a substitute for bank branches. This is similar to the conclusion in Tahsin et al (2018).

Overall, the leapfrog variable has the highest positive effect on digital financial inclusion (Digital Inclusion Index). The leapfrog Fintech proxy has a positive correlation with digital financial inclusion (Eq 1), but a negative correlation with traditional financial inclusion and branches. Taken together, our results suggest that economies with a greater propensity for technological leapfrogging in moving to cellular technologies have also tended to see falling levels of traditional financial infrastructure, particularly in bank branches. The phenomenon of leapfrogging is readily observable in developing countries which have led the way in many innovations such as mobile payments (Kenya), digital land registration (India), and e-commerce (China). They were able to leapfrog because they were not bogged down by legacy IT systems or antiquated infrastructure. The variable of capital invested has only a 10% significance on digital financial inclusion (Eq 3).

Table 3 also shows results for the amount of funds raised through P2P lending platforms as a percentage of GDP. Like leapfrogging, P2P lending has a negative effect on branches (Eq 1). It has a positive correlation with the Digital Intelligence Index (Eq 7), but no significant relationship with the Digital Financial Inclusion Index (Eq 6). This means that P2P lending is complementary to traditional bank lending but a substitute for branches. This result is consistent with previous studies in this area as highlighted in our literature review. As mentioned earlier, lending, as opposed to accounts, is the area with the biggest gap; P2P lending is helping to fill this gap. Experience from many countries shows that P2P lending provides loans at a faster speed and a lower cost, and without collateral requirements that benefit low-income households and SMEs. In some countries, mobile point-of-sale devices or e-payments have helped SMEs collect electronic payments and subsequently use the documented sales as an indicator of creditworthiness to obtain credit. (See, for example, Beck et al. 2018, Sahay et al. 2020).

Table 3: Leapfrog, Fintech and Digital Financial Inclusion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Digital FI	Branch	Digital FI	DII	Branch	Digital FI	DII	Branch
Population	2.551***	-5.835	1.217***	0.709***	2.395	5.090***	0.649***	2.074
	(0.731)	(5.640)	(0.238)	(0.093)	(10.419)	(1.356)	(0.094)	(8.027)
Regulatory Quality	-0.077	1.180	-0.046	0.056***	1.539	-0.038	0.050***	-1.806
	(0.073)	(1.865)	(0.051)	(0.019)	(2.761)	(0.109)	(0.017)	(1.396)
Credit/GDP	-0.384	8.262***	-0.009	-0.057**	8.860	-0.895**	-0.051	0.870
	(0.243)	(2.062)	(0.091)	(0.022)	(5.528)	(0.357)	(0.037)	(4.265)
Education (secondary)	0.011*	-0.112***	0.002	0.001**	-0.131**	0.014	0.001*	-0.043
	(0.006)	(0.032)	(0.004)	(0.000)	(0.051)	(0.010)	(0.000)	(0.039)
Cellphone/population	0.003***	0.017	0.003**	0.001**	0.016	0.004*	0.001*	0.037**
	(0.001)	(0.012)	(0.001)	(0.000)	(0.026)	(0.002)	(0.000)	(0.017)
Internet/population	0.074*	-0.869	0.149***	0.009***	-1.141***	0.012	0.009***	-0.600***
	(0.037)	(0.561)	(0.032)	(0.002)	(0.275)	(0.066)	(0.002)	(0.198)
Leapfrogging (cell/fixed line)	0.037***	-0.172**						
	(0.011)	(0.211)						
Fintech (Capital Invested)			0.013*	0.004***	-0.407***			
			(0.007)	(0.001)	(0.151)			
Fintech (Capital raised, P2P)						-0.014	0.004***	-0.206**
						(0.014)	(0.001)	(0.082)
Constant	-43.450***	88.174	-21.897***	-11.418***	-47.366	-87.686***	-10.407***	-15.840
	(12.088)	(87.108)	(4.237)	(1.570)	(175.158)	(23.514)	(1.548)	(120.189)
Observations	64	950	33	369	332	40	259	307
R-squared	0.786	0.197	0.910	0.692	0.295	0.834	0.678	0.161
Number of ctry	36	152	19	65	71	25	66	85
Adj. R-squared	0.759	0.191	0.884	0.686	0.279	0.797	0.669	0.141

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B. Does Fintech Bridge the Gender, Class and Rural Divides?

We examine the role played by the various Fintech proxies on the various divides, after controlling for the difference in regulatory quality, education, level of trust in the economy and gender inequality across countries. We ran the regression using the latest Digital Intelligence Index sub-indices of rural divide, class divide, and gender divide:

$$XDIVIDE_{it} = \beta_1 + \beta_2 X_{it} + \beta_3 Fintech_{it} + \alpha_i + \varepsilon_{it} \qquad (2)$$

Where XDIVIDE = rural divide or class divide or gender digital divide, 'X's are the control variables: trust index, regulatory quality, and education. Regulatory quality and education appear again in this empirical analysis as they can affect both the level and the gap in digital financial inclusion. Nonetheless, for the equation on the gender divide regression, we added the gender inequality index, to control for "environmental factors" that could disadvantage women. The gender inequality index is a proxy for human development for women. It measures inequality across the three dimensions of health, empowerment, and the labour market.

As shown in Tables 4, 5 and 6, the Fintech proxies are significant and negatively correlated with the rural divide and the class divide. These results imply that Fintech has the potential to improve the rural divide and class divides. However, Fintech has no significant correlation with the gender divide (Table 6). We also checked the robustness by using the raw gap measure without normalization (e.g., digital payments (female) – digital payments (male)). The results are similar and are set out in Appendix C.

Our results demonstrate evidence of the potential benefits of mobile money accounts in providing much-needed digital financial services to lower-income households and small and medium-sized enterprises (SMEs). In many countries, digital financial services have facilitated the quick and efficient deployment of government support measures to firms and households affected by the COVID-19 pandemic.

Table 4: Fintech and Rural Divide in Digital Financial Inclusion

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Rural Divide	Rural Divide	Rural Divide	Rural Divide	Rural Divide
Regulatory quality	-0.019	-0.209	0.222	0.222	-0.190
	(0.292)	(0.398)	(0.246)	(0.209)	(0.173)
Education	-0.000	-0.027	0.009	0.002	-0.001
	(0.003)	(0.067)	(0.022)	(0.003)	(0.005)
Trust index	-0.382***	-0.024	0.193	-0.040	0.170
	(0.076)	(0.129)	(0.201)	(0.203)	(0.253)
Leapfrog	-3.039*				
	(1.754)				
Digital financial inclusion		-4.948**			
		(2.077)			
Digital adoption index			-7.138**		
			(3.054)		
Fintech (Capital invested)				-0.094**	
				(0.045)	
Fintech (Capital raised, P2P)					-0.069**
					(0.030)
Constant	0.274	4.844	3.409	-1.251**	0.363
	(0.283)	(6.945)	(3.242)	(0.568)	(0.571)
Observations	147	32	62	137	98
R-squared	0.286	0.511	0.355	0.234	0.219
Number of ctry	23	8	23	23	23
Adj. R-squared	0.266	0.439	0.310	0.211	0.185

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

However, the story is not so rosy for the gender divide (Table 6). There is no significant correlation between the gender divide and the different Fintech proxies. This is consistent with the findings in Cheah et al. (2021) that the gender gap persists in digital payments.

The digital gap could be explained by differences in preferences across genders, for example differences in risk aversion (Croson and Gneezy, 2009), or differences in the costs and benefits that consumers attach to the use of these new products. They could also result from gender-based discrimination (Bartlett et al., 2019), such as women's previous negative experiences with financial institutions (Brock and De Haas, 2021). Finally, the gap could also arise from social norms or laws that affect the cost-benefit trade-off differently across genders (Hyland et al., 2020). Future research focusing on the determinants of these factors could be particularly promising in understanding the Fintech gender gap.

Table 5: Fintech and Class Divide

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Class Divide	Class Divide	Class Divide	Class Divide	Class Divide
Regulatory quality	0.202	0.320*	0.434***	0.264	0.223
	(0.146)	(0.165)	(0.137)	(0.248)	(0.239)
Education	-0.002	0.052***	0.039**	0.004	-0.003
	(0.002)	(0.011)	(0.016)	(0.003)	(0.004)
Trust index	-0.575***	-0.438***	-0.259***	-0.557**	-0.153
	(0.159)	(0.038)	(0.050)	(0.202)	(0.129)
Leapfrog	-2.357***				
	(0.424)				
Digital financial inclusion		-3.857***			
		(0.365)			
Digital adoption index			-6.282***		
			(1.138)		
Fintech (Capital invested)				-0.056***	
				(0.019)	
Fintech (Capital raised, P2P)					-0.060***
					(0.015)
Constant	0.196	-2.798**	-0.424	-1.023*	0.289
	(0.266)	(1.100)	(1.575)	(0.508)	(0.439)
Observations	147	32	62	137	98
R-squared	0.450	0.917	0.648	0.307	0.477
Number of ctry	23	8	23	23	23
Adj. R-squared	0.434	0.904	0.624	0.286	0.455

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Fintech and Gender Digital Divide

	(1)	(2)	(3)
VARIABLES	Gender Digitial Divide	Gender Digitial Divide	Gender Digitial Divide
Regulatory quality	-0.416*	-0.443**	-0.416**
	(0.211)	(0.197)	(0.189)
Education	0.043	0.003	-0.002
	(0.030)	(0.002)	(0.006)
Trust index	-0.087	-0.155	-0.105
	(0.096)	(0.098)	(0.097)
Gender inequality	4.555	3.553	1.561
	(4.250)	(2.113)	(3.623)
Digital adoption index	-0.882		
	(1.225)		
Fintech (Capital invested)		0.013	
		(0.012)	
Fintech (Capital raised, P2P)			-0.004
			(0.008)
Constant	-4.951	-0.977*	-0.104
	(3.410)	(0.490)	(0.415)
Observations	41	137	98
R-squared	0.325	0.307	0.222
Number of ctry	23	23	23
Adj. R-squared	0.229	0.281	0.180

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A caveat is that the explanatory powers of these variables are rather low and suggest for further analysis with more variables. This is a topic for further research as new data become available.

VI. Policy Implications

Our results above show that while fintech is positively correlated with improving digital financial inclusion, and potentially benefitting the poor and rural population, it could not address the gender divide. To identify the policy measures that could help address the gender gap, we approach several central bankers in the region for their take on this issue (See Appendix 6 for the interview questions). Our interviews with the central bankers in Asia suggest that even in countries with a very high level of traditional financial inclusion, digital financial inclusion is still a work in progress. In many countries, digitalization efforts are decentralized, making it challenging to design an overarching strategy to reduce financial exclusion amongst vulnerable groups. Recognizing the need to narrow the digital gap, especially amongst women and the aged, they have taken a two-track approach: to go digital for those who are both willing and able, and to make sure that those who are willing but unable have continued access to cash and personalized help. As one policymaker put it, the aim is to be cash-light but not completely cashless. Many countries have devised innovative ways to encourage and incentivize digital adoption. For example, in Singapore the “Go Digital Campaign” provides funding support to SMEs to digitalize their business, the “Hawkers Go Digital” provides cash incentives for hawkers to adopt digital payments, and the “Seniors Go Digital Campaign” provides one-on-one guidance to seniors on using mobile phones for digital payments and other digital services. Closing the digital gaps also includes raising financial and digital literacy, addressing infrastructure issues such as broadband and wifi availability, and last-mile challenges.

VII. Conclusion

A higher level of financial inclusion will be achieved when policies succeed in extending financial services to a broader segment of the population in an efficient and sustainable manner. This paper draws three conclusions. First, Fintech has a positive correlation with financial inclusion, and the correlation is greater when digital financial inclusion measures are used as compared to traditional measures. Second, Fintech has played a positive role in bridging the digital access gap between rural and rich-poor populations. Third, Fintech has no correlation with the gender digital gap.

Our findings highlight the importance of leaving no one behind when promoting Fintech services. While Fintech has delivered some promises in reducing the rural, rich-poor gap, more work needs to be done to close the gender gap in access to financial services. Fintech development may need to be complemented by targeted policy initiatives aimed at improving women's access to internet, addressing differences in attitudes or challenges across demographic groups. These challenges include discrimination or social norms and laws that disadvantage women in many countries.

Appendix A. Data Definitions and Source

Leapfrog: Ratio of mobile phones to fixed lines (Source: GSMA)

Capital Invested: Amount of venture capital raised (all stages) for Fintech companies (Source: Pitchbook)

Business Volume: Total amount of funds raised through digital lending and digital capital raising activities. It includes both lending to individuals and businesses and other entities that raise funds via an online digital marketplace. (Source: Cambridge Centre for Alternative Finance)

Gender inequality: It measures gender inequalities across three aspects: (1) reproductive health, measured by maternal mortality ratio and adolescent birth rates; (2) empowerment, measured by proportion of parliamentary seats occupied by females and (3) proportion of adult females and males aged 25 years and older with at least some secondary education; and economic status, expressed as labour market participation and measured by labour force participation rate of female and male populations aged 15 years and older. (Source: UNDP Human development report)

Internet Pop: Per cent of population that has access to the internet (Source: World Bank Findex)

Cell Pop: Per cent of population that has cellphones (Source: World Bank)

Lnpop: Log (Population) (Source: World Development Indicators)

Lcreditgdp: Log (domestic credit by financial institutions/GDP – proxy of financial sector development (Source: IMF)

Mobile money: a pay-as-you-go digital medium of exchange and store of value using mobile money accounts which are offered by a mobile network operator or another entity in partnership with a mobile network operator. (Source: GSMA)

Regulatory quality (req): perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. One of six dimensions of governance in the Worldwide Governance Indicators. (Source: World Bank)

Education: Gross enrollment ratio in secondary school (Source: World Bank World Development Indicators)

Trust index: Edelman Trust Barometer (Source: Edelman), based on survey data covering 22 markets (Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Ireland, Italy, Japan, Malaysia, Mexico, Netherlands, Russia, Singapore, South Korea, Spain, the UAE, the UK, and the US) across 16 industries.

The following are the definitions of the components of the Digital Intelligence Index by the Fletcher School:

Digital Inclusion: The extent to which inequities in digital account ownership, online engagement, and digital payment uptake exists across gender, class, and geography.

Gender Digital Divide: The gap between women and men's usage of digital account, online engagement and digital payment. For instance, the use of digital payments by women divided by the use of digital payments by men. The results are then standardized (z-scored). A negative score means a score below the population mean. The higher the score the better. However, for ease of interpretation, we have reversed the signs in our regressions so that a lower number (i.e. a smaller gap).means an improvement

Class Digital Divide: The extent to which inequities in digital account ownership, online engagement, and digital payment uptake differs among the poorest 40% of the population as compared to the richest 60%. For example, the use of digital payments by the poorest 40% divided by the use of digital payments by the richest 60%. A higher number means higher inclusion. However, for ease of interpretation, we have reversed the signs in our regressions so that a lower number (i.e. a smaller gap).means an improvement

Rural Digital Divide: The extent to which inequities in digital account ownership, online engagement, and digital payment uptake differs between rural consumers vs the average level for a particular country-year. The results are then standardized (z-scored). A negative score means a score below the population mean. The higher the score the better. However, for ease of interpretation, we have reversed the signs in our regressions so that a lower number (i.e. a smaller gap).means an improvement

World Bank Findex Data

% Used the internet to pay bills or to buy something online in the past year (poorest 40%)
% Received digital payments in the last year (poorest 40%)
% Account (poorest 40%)
% Made digital payments in the last year (poorest 40%)
% Used the internet to pay bills or to buy something online in the past year (richest 60%)
% Received digital payments in the last year (richest 60%)
% Account (richest 60%)
% Made digital payments in the last year (richest 60%)
% Used the internet to pay bills or to buy something online in the past year (Male)
% Received digital payments in the last year (Male)
% Account (Male)
% Made digital payments in the last year (Male)
% Used the internet to pay bills or to buy something online in the past year (Female)
% Received digital payments in the last year (Female)
% Account (Female)
% Made digital payments in the last year (Female)
% Used the internet to pay bills or to buy something online in the past year (Urban)
% Received digital payments in the last year (Urban)
% Account (Urban)
% Made digital payments in the last year (Urban)
% Used the internet to pay bills or to buy something online in the past year (Rural)
% Received digital payments in the last year (Rural)
% Account (Rural)
% Made digital payments in the last year (Rural)

Appendix B: Methodology Underlying the Compilation of the Indices

Digital Intelligence Index and the World Bank Digital Adoption Index

The Digital Intelligence Index

Digital Evolution is a data-driven holistic evaluation of the progress of the digital economy across 90 economies, combining 160 different indicators into four key drivers: supply conditions, demand conditions, institutional environment, and innovation and change.

To create a composite picture of the digital economy, Digital Evolution tracks a total of 160 indicators to measure the current state and pace of digitalization. It is structured at four levels: indicators, clusters, components, and drivers. Indicators are standardized data points that answer a specific question. They are aggregated into clusters which illuminate 35 aspects of digitalization and then rolled into 13 higher-order components which ultimately feed into the four drivers. A visual representation of Digital Evolution's data hierarchy is presented here.

The central hypothesis of Digital Evolution is that digitalization of an economy is governed by four drivers of equal importance: supply conditions, demand conditions, institutional environment, and innovation and change. As such, our model accords equal weight to all four drivers. Indicator, cluster, and component weights are determined according to three factors: data quality, data centrality, and the strength of data collection methods.

After indicators have been aggregated into clusters, components, drivers, and ultimately final scores, the final scores are rescaled to fit a 0 to 100 range. Momentum scores are generated by applying the compound annual growth rate formula **(CAGR)** on final index scores across our time window. After calculating index growth rates for each economy, we rescaled CAGRs on a similar 0 to 100 scale. Momentum scores, like the final index scores, are relative.

Throughout the computation, weighting, standardization and aggregation processes we adopted several quality assurances measures to ensure the validity and robustness of the index. By deploying different statistical tools throughout the process, including data cleaning, variance analysis, regression analysis, and simulations, we stress tested the index scores at multiple levels to produce the most comprehensive and robust numbers possible.

The World Bank Digital Adoption Index is a supply-side measure:

The DAI is a worldwide index that measures countries' digital adoption across three dimensions of the economy: people, government, and business. The index covers 180 countries on a 0–1 scale and emphasizes the "supply-side" of digital adoption to maximize coverage and simplify theoretical linkages. The overall DAI is the simple average of three sub-indexes. Each sub-index comprises the technologies necessary for the respective agent to promote development in the digital era: increasing productivity and accelerating broad-based growth for *business*; expanding opportunities and improving welfare for *people*; and increasing the efficiency and accountability of service delivery for *government*. Originally constructed as part of the World

Development Report 2016: Digital Dividends, the DAI has been updated to reflect new data sources and an improved methodology. Two observations are available for most countries: 2014 (applying the updated data and methodology to the year covered in the original DAI dataset), and 2016 (the most recent year available). By measuring the relative adoption of digital technologies, DAI can assist policymakers to design digital strategy with policies tailored to promote digital adoption across different user groups.

Methodology: DAI is a composite index that measures the depth and breadth of adoption of digital technologies in 171 countries, spanning every region and income group. It is based on three sectoral sub-indices covering businesses, people, and governments, with each sub-index assigned an equal weight:

DAI (Economy) = DAI (Businesses) + DAI (People) + DAI (Governments)

- DAI (Business): The Business cluster is the simple average of four normalized indicators: the percentage of businesses with websites, number of secure servers, download speed, and 3G coverage in the country.

- DAI (People): The People cluster is the simple average of two normalized indicators from the Gallup World Poll – mobile access and internet access at home.

- DAI (Governments): The Government cluster is the simple average of three sub-indices: core administrative systems, online public services, and digital identification. Data for online public services is provided by the UN's Online Service Index. Data for core administrative systems and digital identification was collected by the World Bank. The sixteen indicators used to develop the three sub-indices of the Government cluster are the most critical advantage offered by DAI.

Much of the data was collected as part of the preparation for the WDR 2016. These indicators need to be updated on a regular basis to remain useful. Additional indicators to capture ministry-specific management information systems, such as education, health, and welfare payments, are also required.

The four indicators used to create the Business cluster, while useful, are not enough. Firm -specific variables, such as enterprise resource planning, cloud computing, supply chain management software, and e-purchases and e-sales, are currently available only for advanced economies. They need to be expanded to include the developing world.

The methodology used to construct the DAI provides considerable flexibility to adjust the index to accommodate new digital technologies such as mobile money or big data, as well as to drill down to more disaggregated level (for example, DAI for e-retail or digital ID) as required in different contexts.

Appendix C: Robustness Check With Raw Gap Measure

In addition to the Digital Gender Divide produced by the Fletcher School Index, we used the gap in account, "use internet to pay bill", and "made/received digital payment", collected by the Findex Survey. We calculated the gap in accounts as "% of male with account- % of female with account" for the gender digital gap, and "60% richest – 40% poorest" for the class divide. We then used these gap indicators as dependent variables in the panel regression. The results in Table A1 and Table A2 confirm our earlier findings about gender digital gap and class divide. In some cases, we saw a wider gap as a result of Fintech.

Table A1: Fintech and Gender Digital Divide

VARIABLES	(1) Account	(2) Internet to pay bill	(3) Made/received digital payment	(4) Account	(5) Internet to pay bill	(6) Made/received digital payment	(7) Account	(8) Internet to pay bill	(9) Made/received digital payment
Regulatory quality	-0.065	-0.009	-0.097	-0.071	0.012	-0.114***	-0.034	-0.068	-0.044
	(0.065)	(0.014)	(0.056)	(0.065)	(0.023)	(0.036)	(0.035)	(0.049)	(0.060)
Trust index	-0.056**	0.005	-0.050**	-0.057***	0.009	-0.050***	-0.031	-0.038	0.014
	(0.024)	(0.013)	(0.018)	(0.017)	(0.009)	(0.013)	(0.025)	(0.062)	(0.036)
Gender inequality	1.193	0.228	-0.034	1.266	0.282	-0.380	0.507	-0.445	-0.761
	(1.838)	(0.665)	(1.853)	(1.195)	(0.396)	(1.011)	(0.774)	(0.738)	(0.699)
Digital Financial Inclusion	0.042	0.149**	-0.007						
	(0.097)	(0.055)	(0.229)						
Mobile Money Account				0.114	0.462***	-0.240			
				(0.226)	(0.138)	(0.457)			
Fintech (Capital raised, P2P)							-0.000	-0.001	-0.006
							(0.002)	(0.004)	(0.005)
Constant	-0.417	-0.136	0.109	-0.377	-0.139	0.305	-0.040	0.229	0.302
	(0.770)	(0.262)	(0.823)	(0.478)	(0.155)	(0.418)	(0.190)	(0.208)	(0.193)
Observations	22	22	22	24	24	24	51	51	51
R-squared	0.328	0.331	0.130	0.428	0.460	0.192	0.117	0.070	0.102
Number of ctry	11	11	11	12	12	12	27	27	27
Adj. R-squared	0.169	0.173	-0.0750	0.307	0.346	0.0216	0.0405	-0.0112	0.0235

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Fintech and Class Digital Divide

VARIABLES	(1) Account	(2) Internet to pay bill	(3) Made/received digital payment	(4) Account	(5) Internet to pay bill	(6) Made/received digital payment	(7) Account	(8) Internet to pay bill	(9) Made/received digital payment
Regulatory quality	0.117**	0.069	0.065**	0.088*	0.058	0.027	0.078**	0.049	0.057
	(0.047)	(0.041)	(0.028)	(0.046)	(0.059)	(0.030)	(0.033)	(0.054)	(0.054)
Trust index	-0.066**	-0.003	-0.013	-0.078***	0.016	-0.041*	-0.103***	-0.009	0.021
	(0.021)	(0.021)	(0.014)	(0.018)	(0.039)	(0.020)	(0.032)	(0.053)	(0.050)
Gender inequality	1.167	-0.193	-1.590	0.743	0.898	-1.092	0.358	0.047	-1.066
	(1.734)	(1.108)	(1.249)	(1.142)	(1.284)	(1.095)	(0.683)	(0.807)	(0.891)
Digital Financial Inclusion	0.020	0.393***	-0.283						
	(0.178)	(0.121)	(0.161)						
Mobile Money Account				-0.016	1.051**	-0.301			
				(0.274)	(0.445)	(0.416)			
Fintech (Capital raised, P2P)							0.001	0.005	-0.007
							(0.003)	(0.006)	(0.005)
Constant	-0.282	0.024	0.887	-0.115	-0.361	0.571	-0.005	0.050	0.352
	(0.743)	(0.460)	(0.549)	(0.449)	(0.505)	(0.441)	(0.170)	(0.219)	(0.234)
Observations	22	22	22	24	24	24	51	51	51
R-squared	0.304	0.610	0.460	0.296	0.279	0.116	0.217	0.048	0.128
Number of ctry	11	11	11	12	12	12	27	27	27
Adj. R-squared	0.140	0.518	0.333	0.148	0.127	-0.0701	0.149	-0.0343	0.0518

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix D: Interview Questions with Policymakers

- In the design of the digitalization/fintech national strategy, have you considered the segments of society that might be excluded e.g. the poor, aged, women, those in rural/remote areas?
- Who amongst the "excluded group" do you think are the most excluded and therefore needs most help?
- How do you take into account these gaps and what needs to be done to help those excluded or make sure that they can catch up?
- What are the consequences of ignoring this group?
- Would you consider slowing the pace of fintech development in your country as part of your strategy to "wait" for them to catch up.
- Would additional data initiatives help in the design of policies to mitigate financial exclusion? If so, any specific examples?

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PUBLICATIONS

Fintech: Financial Inclusion or Exclusion?
Working Paper No. **WP/2022/080**

How Financial Digitalization Affects Business Performance and Business Innovation among Ultra-Micro, Micro, and Small Enterprises: Evidence from Indonesia[1]

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Abstract

The COVID-19 pandemic and the associated mobility restrictions have induced many ultra-micro, micro, and small enterprises (UMSEs) to move online and utilize digital finance to survive and thrive. We investigate the impact of the financial digitalization of UMSEs on their business performance and business innovation using data from Bank Indonesia's UMSEs digital adoption survey in 2023, which covers more than 5,000 enterprises in Indonesia. To identify causality, we employ the inverse probability weighting regression adjustment (IPWRA) method. The findings indicate that financial digitalization improves UMSEs' business performance and business innovation. These findings confirm the significant role of technology-driven innovation in financial services in the development of small businesses. However, several key challenges need to be addressed first, particularly digital financial literacy, integrated infrastructure, and regulations. Therefore, policy actions to accelerate UMSEs' digital transformation are needed to help them achieve high productivity, long-term growth, and global competitiveness.

Keywords: financial digitalization; ultra-micro, micro, and small enterprises; business performance; business innovation; Indonesia

JEL Codes: G20, D22, O16, O33

[1] With the usual disclaimer, we thank Bank Indonesia Insititute for providing the data for this study. Corresponding author: Masagus M.Ridhwan. Email: mha_ridhwan@bi.go.id

1. Introduction

Micro, small, and medium enterprises (MSMEs) make up about 90% of enterprises, employ 70% of workers, and contribute to 50% of the gross domestic product (GDP) in the world (UNCTAD, 2022). Therefore, MSMEs are often hailed as the backbone of economies worldwide. The low contribution of MSMEs to GDP relative to their employment contribution is due to their lower productivity compared to large enterprises. Hence, increasing the productivity of MSMEs is a major challenge for the world economy. If MSMEs' productivity can be increased meaningfully, the world's GDP will increase significantly, raising the welfare of the majority of workers and their families.

The COVID-19 pandemic and the associated mobility restrictions have forced many MSMEs to exit. Meanwhile, surviving enterprises have to deal with a changing business landscape, with many patterns of sales, distribution, and consumer behavior having been substantially and permanently altered (UNCTAD, 2022). However, Igarashi et al. (2021) found a wide variation in the severity of and responses to the pandemic impacts on MSMEs between sectors and countries. In response to this changing environment, many MSMEs have moved online and sought to enhance their ability to access markets using digital technology (UNCTAD, 2022). This jump in digitalization, including financial digitalization, among MSMEs raises the question of whether it leads to productivity and performance improvements in MSMEs.

MSMEs face significant challenges, notably due to their limited access to financial services, creating a financing gap that impedes their growth and productivity (Beck & Demirguc-Kunt, 2006). This gap stems from various factors, including the high costs financiers face in reaching and servicing MSMEs compared to larger corporate clients (Diamond, 1984). Furthermore, some intrinsic characteristics of MSMEs, such as their small size, relative youth, and lack of financial literacy, exacerbate the challenges. In this context, financial digitalization emerges as a promising solution, potentially transforming MSME financing through technological advancements. Even more, financial services digitalization jumped significantly when the stay-at-home order policy was imposed due to the pandemic, notably in emerging countries like Indonesia (see, e.g., Ridhwan et al., 2024).

Digital financial services (DFS) could tackle various market failures obstructing financial inclusion in developing regions in several ways. First, they lower the transaction costs associated with basic banking and money transfer services through digital technology. Second, digital finance based on data utilization bridges the information gaps that often obstruct market efficiency. Lastly, financial digitalization paves the way for innovative service delivery models, revolutionizing the approach to financial services (Moorena et al., 2020).

The role of digital finance and technology is crucial in streamlining the process of matching parties in transactions, leveraging big data for economies of scale, and ensuring the transmission of information is both cost-effective and secure. Additionally, these technologies are instrumental in reducing the costs associated with verifying transactions (Allen et al., 2021). Furthermore, digitalizing payment systems in retail and wholesale is closely linked to increased financial outreach and depth, suggesting its pivotal role in alleviating credit market frictions and expanding credit availability to MSMEs (Huang et al., 2019).

Emerging digital technologies are also making financial services more accessible and cost-effective for MSMEs and other groups that have historically been underserved by traditional financial systems (Buchak et al., 2018). Balyuk et al. (2022) investigated peer-to-peer (P2P) lending's impact on credit access, finding that financial technology (fintech) lenders enhance credit availability for consumers who are ineligible for traditional bank loans. In a similar vein, Beck et al. (2018) analyze the effects of payment technology innovation on entrepreneurship and economic development and conclude with the importance of comprehensive strategies focused on improving access to financial services, including payment services, to mitigate financial constraints and enhance business performance.

Several previous studies have shown the impact of financial digitalization on the productivity and performance of MSMEs. Financial digitalization can assist MSMEs in increasing their productivity by enhancing production efficiency, lowering operational expenses, and responding rapidly to market demand. Additionally, it can aid enterprises in achieving cross-border integration, exploring new business fields, boosting innovation capabilities, and improving market competitiveness (He & Wang, 2023). Furthermore, digital finance can effectively alleviate the financing constraints of MSMEs by alleviating the phenomenon of financial exclusion in the traditional financial market, lowering the entry threshold for MSME credit, fostering a favorable financial environment, and better matching the financing needs of MSMEs' technological innovation projects.

Hence, digital finance can promote technological innovation in MSMEs. The higher the degree of digitalization, the more pronounced the promotion effect. Digital finance improves the financial performance of MSMEs by expanding the scale of innovative investment, reducing the cost of debt financing, and strengthening risk-taking ability. Unlike traditional financial policies that often sideline MSMEs due to perceived risks, digital finance enhances the ability of financial institutions to assess the actual needs and potentials of these enterprises accurately. This advanced technology enables better tracking and analysis of MSME activities, facilitating more informed lending decisions. By providing a clearer picture of MSMEs' innovation ventures, which typically involve higher risks and uncertain outcomes, digital finance increases banks' readiness to extend credit. Consequently, this shift is essential in broadening the financial institutions' will to facilitate credit for helping induce innovative actions circulating in MSME's operations.

In this paper, we investigate the impact of financial digitalization (based on digital banks, e-wallets, and fintech) of ultra-micro, micro, and small enterprises (UMSEs) on their business performance and business innovation. Using Bank Indonesia's digital adoption survey data in 2023 which covers more than 5,000 UMSEs in 201 out of 514 districts in 17 out of 34 provinces spread over all the major islands of Indonesia. The surveyed area represents approximately 80% of the nation's economic activities. From this survey, we could also separate the smallest micro enterprises into a different category, called the ultra-micro enterprises, as they have a distinct behavior from the larger micro-enterprises. Besides the unique data, another important contribution of this study is that it is among the first to estimate the causal relationship of financial digitalization on the business performance and business innovation of UMSEs in a large developing economy, Indonesia.

Using the inverse probability weighting regression adjustment (IPWRA) method, we find that financial digitalization increases UMSEs' business performance in terms of revenue per worker, revenue growth, and number of employees. Likewise, financial digitalization also boosts UMSEs' business innovation in terms of the probability of having out-of-town customers, the proportion of those out-of-town customers, the likelihood of engaging in exporting activities, and product diversification. Finally, this paper also finds some heterogeneous impacts of financial digitalization across different demographic characteristics and geographical locations.

Based on the findings, we provide policy recommendations to support digital transformation among UMSEs, notably the development of their financial services, and to address those challenges in UMSEs' business development. Additionally, the findings offer valuable insights for other economies undergoing similar transitions. The next section highlights Indonesia's financial digitalization development, followed by a data and methodology review section. The last sections discuss the findings and conclusion.

2. MSME Financial Digitalization in Indonesia

MSMEs play a critical role in the Indonesian economy. According to data from the Ministry of Cooperatives and SMEs in 2021, there are 64.2 million MSMEs, contributing 61.1% to the nation's GDP. Importantly, MSMEs are major employment providers, employing 97% of the nation's workforce, comprising approximately 117 million workers. Notably, 64.5% of this workforce consists of women.[2]

During the COVID-19 pandemic, an LPEM and UNDP (2020) study revealed that more than 45% of MSMEs faced problems obtaining raw materials, and 90% faced lower demand for their products, leading to business closures. However, as Shinozaki (2022) suggested, the COVID-19 crisis and mobility restrictions have pushed many MSMEs in Indonesia to accelerate digitalization. Ridhwan et al. (2023) found that the fast growth of e-commerce during the pandemic generates employment opportunities primarily in the form of self-employment, notably UMSEs. This finding underscores the critical role of e-commerce as an employment buffer during the crisis.

Regarding finances, Indonesian MSMEs face some notorious capital difficulties. Commonly, they face limited access to appropriate credit financing, as their businesses are managed traditionally, encounter skill gap issues, lack official business permits and financial records required for bank loan administrations and hardly have collateral assets.[3] The vast geographical structure of the Indonesian archipelago, while transportation and telecommunication

[2] For further details, see https://www.bi.go.id/en/publikasi/laporan/Documents/8.LPI2020_Bab_6_en.pdf
[3] See, https://www.weforum.org/agenda/2022/05/digitalization-growth-indonesia-msmes/

infrastructures are pretty limited, has led to unequal money in circulation, and the bank's payment system is unequally distributed throughout the country. Consequently, with 70% of total small businesses lacking access to credit and only 6% of them having bank loans, it results in a large financing gap that has emerged as a structural impediment to inclusive growth and unequal regional development in Indonesia over time.[4]

The rapid rise of digitalization in financial services, predominantly in the post-pandemic era, has become an alternative source of financial services needed by MSMEs, especially those that cannot access mainstream services, notably banks. The most common types of digital financial services (DFS) used locally are digital banks, e-wallets (digital payment), and peer-to-peer (fintech) lending.[5] Digital banks primarily provide financial services through virtual channels, such as mobile apps and websites. This strategy enables them to reach a broader audience without depending on physical branches. Meanwhile, digital payments refer to payments that take place using digital channels or online modes, with no exchange of hard cash being involved, and mostly, they include (e-wallet) mobile payment apps, bank transfers, and wire transfers.

In 2019, Bank Indonesia introduced cashless payment systems through the Quick Response Code Indonesia Standard (QRIS).[6] Likewise, fintech, characterized as technology-driven innovation in financial services, is increasingly crucial in providing more convenient and accessible services and improving credit risk evaluations. These instruments could be a unique opportunity for projects that may be too small, too risky, or serve a social purpose.

[4] https://www.elibrary.imf.org/downloadpdf/journals/002/2021/047/article-A006-en.pdf
[5] See, for example, He & Wang (2023); Moorena et al, (2020); Batunanggar (2019) among others.
[6] The main advantage of QRIS is its ability to universalize digital payments in Indonesia by facilitating interoperability among various digital payment system service providers, while also showcasing its other potential use cases.

The adoption of digital financial services has supported the e-commerce surge since the pandemic. In 2023, the value of Indonesia's e-commerce transactions was estimated to have reached Rp533 trillion (approximately US$34.35 billion), which has increased almost thirteen times from 42 trillion rupiahs recorded in 2017.[7] As of August 2022, the number of micro, small, and medium enterprises (MSMEs) that have joined the Indonesian digital ecosystem has reached 20.24 million, or about 32% of the total number of enterprises. E-commerce continues to be a significant driving force in Indonesia's digital economy, and it is projected to contribute a Gross Merchandise Value (GMV) of $95 billion by 2025.

The rapid expansion in e-commerce is facilitated by digital payment services, which in turn creates a lively market for fintech e-money issuers, and they are largely dominated by a small number of major players.[8] Nearly one-third of e-commerce transactions are conducted using mobile and online payment platforms offered by fintech firms.[9] As of end-2023, there are five biggest e-commerce platforms, which will have approximately 131 million users by 2028, and there are more than 334 fintech players operating nationally.[10] Bank Indonesia also reports that digital banking transactions (mostly ATMs, debit cards, QRIS, and bank transfers) continued to flourish, with transaction volume growth of 30.85%, reaching 4.47 billion transactions, and similarly transaction value increased by 13.25% to reach Rp15.87 thousand trillion in the fourth quarter of 2023. Likewise, electronic money (e-money) transactions tracked an upward trend, with transaction volume increasing 11.10% and transaction value growing 7.93% in 2023.

[7] https://jakartaglobe.id/business/ecommerce-transactions-in-indonesia-projected-to-reach-rp-533-trillion-in-2023
[8] They are Gopay, OVO, DANA and LinkAja which are the most widely used e-money services.
[9] Kilay et al. (2022) find that the use of e-payment and e-commerce services has a significant positive influence on the performance of the MSMEs supply chain in Indonesia.
[10] For further details, see https://www.statista.com/topics/5742/e-commerce-in-indonesia/#topicOverview

Despite the recent rapid growth of Indonesian financial digitalization, some fundamental issues remain challenging for its future development (Siregar et al., 2022). First, many UMSEs, particularly in rural and remote areas, still lack digital and financial literacy. Digital literacy involves using digital tools effectively, while financial literacy entails understanding financial principles. This skills gap hinders UMSEs from fully utilizing digital financial services, leading to missed growth opportunities and increased vulnerability to cyber threats. Secondly, Indonesia's digital infrastructure is staggeringly uneven, with more developed regions like Java-Bali having better connectivity than Off Java-Bali regions.[11] Poor internet access in these areas limits UMSEs' participation in the digital economy, exacerbating existing inequalities. Additionally, the lack of formal financial services in these areas forces UMSEs to rely on informal moneylenders, notably loan sharks, that charge interest rates up to or even over 200% to their borrowers. Under the digital platform, illegal loan sharks have also transformed themselves into fintech or P2P lending, hence pushing away UMSEs from utilizing digital financial services.[12] Not to mention, some cybersecurity concerns make UMSEs skeptical about the reliability and security of digital transactions, and this raises the trust issue for early digital adopters like UMSEs (see Affandi et al., 2024).

3. Data and Methodology

3.1. Data

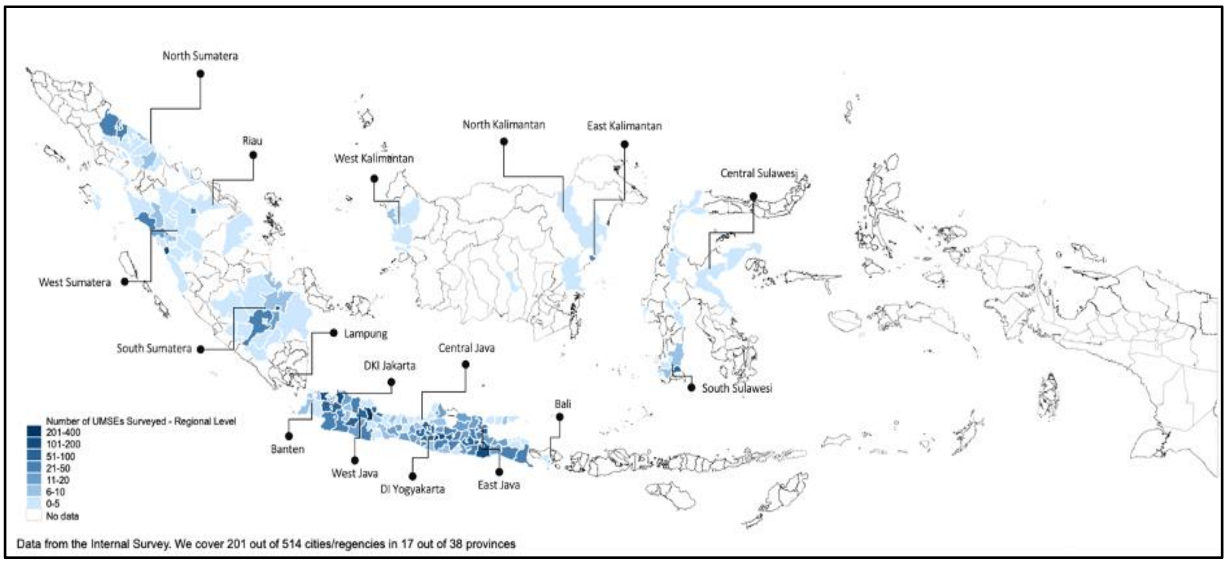
This study primarily utilizes data from the digital adoption survey of micro and small enterprises conducted by Bank Indonesia. The survey covers 5,035 UMSEs through a mix of in-person and

[11] see, https://en.wikipedia.org/wiki/Provinces_of_Indonesia
[12] See, https://www.business-humanrights.org/en/latest-news/indonesia-online-loan-sharks-intimidate-and-harass-borrowers-activists-call-for-better-regulations/

online questionnaires during June-September 2023. Employing a multistage sampling approach, the survey combined quota sampling at the provincial level with convenience sampling to ensure diverse representation across business sectors, geographical locations (urban/rural), and enterprise sizes.

The survey was conducted in 201 districts in 17 provinces throughout Indonesia, accounting for around 80% of the nation's economic activities. The areas surveyed include Sumatera island (North Sumatera, West Sumatera, Riau, Lampung, and South Sumatera), Java-Bali islands (DKI Jakarta, Banten, West Java, Central Java, DI Yogyakarta, East Java, and Bali), Kalimantan island (West Kalimantan, East Kalimantan, and North Kalimantan), and Sulawesi island (South Sulawesi and Central Sulawesi).

Figure 1. Spatial map of the survey respondents' distribution



Source: Bank Indonesia's Digital Adoption Survey (2023)

The districts included in the survey are shown in Figure 1. The shading on the figure indicates the intensity of surveyed UMSEs within different districts. Darker shades represent a higher number of surveyed UMSEs, which can be seen prominently in Java-Bali Island, particularly in and around the capital city, DKI Jakarta, and other major urban centers in West Java and East Java provinces.

For the categorization of UMSEs, we determined groupings based on their revenue in the last financial year, in compliance with the Indonesian government regulations (PP No. 7/2021[13]). Enterprises are categorized into three segments: ultra-micro, micro, and small enterprises, as detailed in Table 1. Ultra-micro enterprises are defined as those with annual revenue below Indonesian Rupiah (IDR) 250 million, micro-enterprises have annual revenue between IDR 250 million and 2 billion, and small enterprises have annual revenue of IDR 2-15 billion.

Table 1. The UMSE criteria and its sample distribution

Type of Enterprise	Revenue Criteria (IDR)	Number of Observation	Share	Reference
Ultra-micro enterprise	Maximum 250 million	3,973	78,91%	Novelty of this study
Micro enterprise	>250 million – 2 billion	921	18,29%	Indonesian government regulation (PP No.7/2021)
Small enterprise	>2 – 15 billion	141	2,80%	

Based on the survey result, 78.9% of enterprises reported annual revenue of up to IDR 250 million, so they are grouped into ultra-micro enterprises. Micro enterprises constitute 18.29% of the sample, while small enterprises represent only 2.80% of the total sample. We treat ultra-micro enterprises as a separate segment, and their significant presence in the sample highlights a novel area of this study. We aim to provide new insights into this smallest scale of business, which is often overlooked in policy and academic research despite their sizable portion.

[13] For further details, see https://jdih.setkab.go.id/PUUdoc/176384/PP_Nomor_7_Tahun_2021.pdf

3.2. Key variables

As aforementioned, we follow the common term financial digitalization or digital financial services here, including digital banks, e-wallet/e-payment, and online lending such as peer-to-peer lending and financial technology. The UMSEs are defined as financially digitalized if they utilize at least one of the digital financial services. Business performance is proxied using five indicators: revenue per worker, cost per worker, profit per worker, revenue growth, and number of employees. Regarding business innovation, we use four indicators to represent innovative business activities: having out-of-town customers, the proportion of those out-of-town customers, engaging in exporting activities, and product diversification.

To control for confounding factors associated with the outcome variables, first, we control for the owners' characteristics, which include the owners' education, age, and gender. Next, we use the signal strength measured from the average upload and download speed across the district level in the survey, registering levels of megabytes per second (Mbps). Businesses with good internet connections are more likely to market their products extensively. Following Falentina et al. (2021), to address any statistical biases, we factor in the number of local Base Transceiver Stations (BTS) in a district, which cellular companies predominantly determine, capturing potential variances in signal strength across areas.

3.3. Empirical method

Our main goal is to estimate the causal impact of financial digitalization on UMSEs' business performance and business innovation. A critical aspect of our analysis involves addressing the concern of endogeneity in the relationship between financial digitalization with business performance and business innovation, and in doing so, we resort to utilizing a "matching" technique. Given the non-random nature of financial digitalization adoption, there may be differences between enterprises that have adopted digital financial services and those that have not. Such differences can lead to biased estimations if a straightforward comparison of mean outcomes is performed. Matching is a statistical technique used to evaluate the effect of an intervention in observational studies by comparing treatment and control units (Stuart, 2010). It involves estimating the similarities between observations and selecting a method to align similar units across intervention groups. Some matching methods that are commonly used include nearest-neighbor matching (NNM), propensity score matching (PSM), inverse probability weighting (IPW), regression adjustment (RA), and inverse probability weighting regression adjustment (IPWRA). NNM and PSM aim to directly match observations based on characteristic closeness, while IPW, RA, and IPWRA apply statistical adjustments.

The advantage of using IPWRA, which combines the IPW model of treatment status (i.e., financial digitalization adoption) with the RA model of outcomes, is that it offers a doubly robust property. This means IPWRA only requires correct specifications of either the treatment or outcome model to achieve an unbiased estimation. This is an advantage over methods like NNM and PSM, which may significantly reduce the sample size due to unmatched units (Wooldridge, 2007; Słoczyński and Wooldridge, 2018). Therefore, we select IPWRA as the preferred method for this study.

The IPWRA method involves a three-step process to estimate treatment effects:

1) Estimating treatment model parameters to derive inverse probability weights for each observation’s likelihood of treatment adoption.
2) Using these weights in the RA process to model outcomes across treatment levels and predict outcomes for each observation.

3) Calculating mean predicted outcomes to estimate the average treatment effect (ATE) of financial digitalization.

To establish causal effects, it is crucial to adjust for variables affecting both the likelihood of adopting digital financial services and the outcomes. The control variables used are selected by considering some requirements: (1) the variables affect the possibility of adopting financial digitalization and the outcomes; (2) the variables are unaffected by the financial digitalization or the anticipation of adopting financial digitalization (Caliendo and Kopeinig, 2008). The success of IPWRA hinges on the conditional independence assumption, which posits outcome variables are independent of treatment after propensity score weighting, and the overlap assumption, ensuring similar characteristics among treated and untreated units. These assumptions can be investigated through balance and overlap tests.

4. Results and Discussion

4.1. Descriptive statistics

Table A1 in the Appendix shows the summary statistics of UMSEs in the data. Around 64 percent of the UMSEs in the sample have adopted financial digitalization tools. A third of UMSEs have out-of-town customers, indicating market expansion and a broader customer base. The average percentage of out-of-town customers is 8.7%, though with a high standard deviation. The low export numbers indicate limited international reach. Most UMSEs in the sample have owners with a senior high school education, are owned by women, are located in Java-Bali, are self-established, are relatively new, and are led by owners in their mid-30s.

Table A2 in the Appendix presents separate descriptive statistics based on the financial digitalization status. In general, this table shows that UMSEs with financial digitalization exhibit significantly higher averages in various aspects, particularly revenue growth, customer reach, and educational attainment.

4.2. Estimation results

Before proceeding to the IPWRA coefficients, we first assess the robustness of the "matching" process utilized by the IPWRA method. Table A3 in the Appendix displays the standardized differences and variance ratios of covariates between treatment and control groups before and after matching, showing that most of these metrics approach 0 and 1, respectively, after the matching process. Table A4 presents the overidentification test results for the IPWRA process, with a p-value of 0.126. This indicates we cannot reject the null hypothesis that the covariates are balanced after IPWRA estimation. Figure A1 demonstrates that the distribution of continuous covariates becomes more similar post-matching. Overall, the IPWRA process effectively balances covariates between the treatment and control groups.

Table 2. Estimation results using IPWRA and OLS

	Business Performance				Business Innovation				
IPWRA	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Financial Digitalization	0.094***	0.183***	0.034	0.016***	0.478***	0.165***	0.056***	0.008***	0.053***
	(0.035)	(0.037)	(0.037)	(0.004)	(0.079)	(0.014)	(0.005)	(0.002)	(0.014)
Observation	5,017	5,017	5,015	5,017	5,017	5,017	5,016	5,017	5017
OLS	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Financial Digitalization	0.116***	0.190**	0.067*	0.012***	0.526***	0.137***	0.044***	0.003	0.049***
	(0.033)	(0.035)	(0.035)	(0.004)	(0.079)	(0.012)	(0.004)	(0.002)	(0.012)
Observation	5,017	5,017	5,015	5,017	5,017	5,017	5,016	5,017	5017

Note: (1) Revenue per worker, (2) Cost per worker, (3) Profit per worker, (4) Annual sales growth, (5) Number of employees: No employee, 1-5 employees. 6-10 employees, > 10 employees, (6) Dummy of having out-of-town customers, (7) Percentage of out-of-town customers to the total customers, (8) Dummy of exporting products, (9) Diversification.
Robust standard errors clustered at the individual level are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2 presents the IPWRA coefficients from estimations of the impact of financial digitalization on business performance. In addition, the table also provides the estimation results using ordinary least squares (OLS) as a baseline estimation for comparison. We also provide estimation results using Augmented Inverse Probability Weighting (AIPW) in Table A5 and Inverse Probability Weighting (IPW) in Table A6 in the Appendix, which are consistent with the results from IPWRA. These consistent results from various estimation methods indicate that our IPWRA results are robust.

The IPWRA estimation results indicate that, apart from profit per worker, financial digitalization significantly affects various measures of business performance and innovation. It increases revenue per worker by 9.4%, cost per worker by 18.3%, revenue growth by 1.6 percentage points, the number of employees by 0.5 employees, the probability of having out-of-town customers by 16.5 percentage points, the percentage of out-of-town customers by 5.6 percentage points, the probability of exporting by 0.8 percentage points, and product diversification by 5.3 percentage points.

4.3. Heterogeneity analysis

To examine the heterogeneous impacts of financial digitalization across various characteristics, we conducted subsample IPWRA estimations based on gender, age, and location. Table 3 shows that for both male and female-owned UMSEs, the impact of financial digitalization on business performance and business innovation is similar to the main results. This indicates that financial digitalization is critical in enhancing small business outcomes, irrespective of the owner's gender.

Table 3. IPWRA estimation results by gender

	Business Performance				Business Innovation				
A. Male	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial digitalization	0.115**	0.222***	0.048	0.015*	0.489***	0.167***	0.045***	0.008*	0.073***
	(0.057)	(0.059)	(0.059)	(0.007)	(0.155)	(0.020)	(0.078)	(0.004)	(0.019)
Observation	1,871	1,871	1,870	1,871	1,871	1,871	1,871	1,871	1,871
B. Female	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial digitalization	0.085*	0.156***	0.035	0.016***	0.476***	0.165***	0.062***	0.009***	0.041**
	(0.045)	(0.048)	(0.047)	(0.006)	(0.087)	(0.017)	(0.064)	(0.003)	(0.018)
Observation	3,146	3,146	3,147	3,146	3,146	3,146	3,146	3,146	3,146

Note: (1) Revenue per worker, (2) Cost per worker, (3) Profit per worker, (4) Annual sales growth, (5) Number of employees: No employee, 1-5 employees. 6-10 employees, > 10 employees, (6) Dummy of having out-of-town customers, (7) Percentage of out-of-town customers to the total customers, (8) Dummy of exporting products, (9) Diversification.
Robust standard errors clustered at the individual level are in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 4. IPWRA estimation results by age group

	Business Performance				Business Innovation				
A. Below 40 years	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial digitalization	0.038	0.136***	-0.024	0.017***	0.368***	0.183***	0.064***	0.008***	0.062**
	(0.042)	(0.044)	(0.044)	(0.006)	(0.086)	(0.017)	(0.063)	(0.002)	(0.016)
Observation	3,263	3,263	3,262	3,263	3,263	3,263	3,263	3,263	3,263
B. 40 years or above	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial digitalization	0.182***	0.245***	0.139**	0.012	0.476***	0.122***	0.036***	0.008***	0.049**
	(0.064)	(0.065)	(0.069)	(0.008)	(0.087)	(0.023)	(0.091)	(0.002)	(0.023)
Observation	1,754	1,754	1,754	1,754	1,754	1,754	1,754	1,754	1,754

Note: (1) Revenue per worker, (2) Cost per worker, (3) Profit per worker, (4) Annual sales growth, (5) Number of employees: No employee, 1-5 employees. 6-10 employees, > 10 employees, (6) Dummy of having out-of-town customers, (7) Percentage of out-of-town customers to the total customers, (8) Dummy of exporting products, (9) Diversification.
Robust standard errors clustered at the individual level are in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

For UMSEs owned by individuals aged below 40 years, as shown in Table 4, the influence of financial digitalization is more modest on business performance but more pronounced on business innovation. While there is a significant positive effect on revenue growth, the effect does not hold at the level form. Among the older cohort, the impact of financial digitalization on business performance appears to be more pronounced and consistently positive across all performance indicators but less pronounced on business innovation. Notably, there is a substantial effect on revenue per worker, profit per worker, and revenue growth, suggesting that shifting to digital finance may contribute to the scaling and profitability of these older cohort-owned UMSEs. The results indicate a visible age-related heterogeneity in the effects of financial digitalization on UMSEs. Older enterprise owners benefit more from financial digitalization than their younger counterparts in terms of business performance. On the other hand, among the younger entrepreneurs, financial digitalization leads to stronger business innovation than the older business owners.

Table 5 shows the IPWRA results for enterprises located in Java-Bali and off Java-Bali islands. Across both regions, financial digitalization consistently positively impacts business performance and innovation. For business performance indicators, the effects are more discernible outside Java-Bali Island. On the other hand, for business innovation indicators, the effects are stronger in Java-Bali Island, particularly on the likelihood of export.

Table 5. IPWRA estimation results by location

	Business Performance				Business Innovation				
A. Java -Bali	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial digitalization	0.073*	0.182***	0.010	0.009*	0.362***	0.167***	0.055***	0.009***	0.051***
	(0.039)	(0.041)	(0.041)	(0.005)	(0.091)	(0.016)	(0.006)	(0.002)	(0.016)
Observation	3,916	3,916	3,916	3,916	3,916	3,916	3,916	3,916	3,916
B. Off Java -Bali	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial digitalization	0.170**	0.226***	0.117	0.038***	0.598***	0.144***	0.056***	0.003	0.039*
	(0.074)	(0.080)	(0.076)	(0.011)	(0.152)	(0.026)	(0.098)	(0.007)	(0.026)
Observation	1,101	1,1101	1,099	1,101	1,101	1,101	1,101	1,101	1,101

Note: (1) Revenue per worker, (2) Cost per worker, (3) Profit per worker, (4) Annual sales growth, (5) Number of employees: No employee, 1-5 employees. 6-10 employees, > 10 employees, (6) Dummy of having out-of-town customers, (7) Percentage of out-of-town customers to the total customers, (8) Dummy of exporting products, (9) Diversification.
Robust standard errors clustered at the individual level are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4. Discussion

The results of this study provide a comprehensive overview of the impact of financial digitalization on various aspects of UMSEs' business performance and business innovation. The positive effects are widespread, enhancing revenue per worker (productivity), revenue growth, the number of employees, the probability of having out-of-town customers, the percentage of those out-of-town customers, the likelihood of engaging in exporting activities, and product diversification. These enhancements are pivotal for UMSEs looking to expand their market reach and increase operational scales, indicating the transformative potential of financial digitalization.

This finding aligns with Ozili's (2018) and Abbasi and Wigand's (2017), who noted a positive association between access to digital financing and improved business performance. Similarly, the findings of studies by Agyapong and Attram (2019), Hussain et al. (2019), and Okello et al. (2017) have demonstrated that the adoption of digital currencies and the utilization of digital channels for accessing capital contribute to enhancing firm performance and growth. Financial digitalization's advantages serve as a compounding multiplier for the entire business ecosystem; the broader the adoption of digital opportunities by UMSEs, the more significant the socio-economic benefits for the community and the national economy (Siregar et al., 2022). The study has shown that digitalization not only increases the monetary outcome of the business but also allows more people to find job opportunities within UMSEs.

However, the increase in cost per worker by 20 percentage points highlights a notable concern: while digitalization drives revenue and broadens market access, it also escalates operational costs per employee at the first stage of adoption. Building digital infrastructures involves huge and long-term capital investment for internet providers, consequently the internet subscription fees are quite costly for UMSEs and hence, lead to substantial expenses relative to their revenue.

Xiaoyan et al. (2022) explain there are two primary approaches to achieving digital finance transformation in MSMEs. Some opt to build internal capabilities, while others choose to leverage external resources. Regardless of the method chosen, substantial capital and human resources investments are necessary. Initially, significant investments are required in various software and hardware, such as new smartphones or payment gateways. Additionally, the scarcity of digital labor drives up the cost of integrating it by training them to use new digital financial tools and systems effectively. Utilizing "outsourced" services, such as traditional IT services and newer cloud platforms, might incur costs. However, this approach can sometimes lead to ineffective digital investments due to its detachment from industry and business specifics. It raises an important discussion point about the balance between the benefits of financial digitalization and its associated costs, underlining the need for strategic planning to mitigate these expenses.

Furthermore, the lack of significant impact on profit per worker may prompt further investigation. This outcome suggests that the increases in revenue and costs might be offsetting each other, leading to a neutral effect on profit margins per employee. Some researchers suggest that the benefit of digitalizing the UMSE's finances may manifest predominantly over the long term, indicating the positive impact could unfold gradually and accumulate significant advantages as time progresses (Siddik et al., 2016; Van Uyen & Phuong, 2015; Hernando & Nieto, 2007). UMSEs must analyze the specific areas where costs are increasing and assess whether these investments yield long-term benefits surpassing the immediate financial burden.

Delving into the heterogeneity aspect, the more discernible impact of financial digitalization on several outcomes of male-owned small businesses compared to female-owned ones can be attributed to several factors. Research indicates that male entrepreneurs generally have better access to advanced technology and digital tools, enhancing their ability to leverage digital financial services effectively (Orser et al., 2019; Wajcman et al., 2020). Additionally, men often exhibit higher levels of financial literacy and confidence, which facilitates adopting and utilizing these services (Mabrouk et al., 2023). Funding disparities also play a significant role, with male-owned businesses typically receiving more investment, providing the capital necessary to implement digital financial solutions. Networking and mentorship programs, which are crucial for navigating the digital finance landscape, are more readily accessible to male entrepreneurs. Moreover, cultural and societal norms, especially in Indonesia, often encourage and support men more in adopting digital innovations relative to women (SMERU Research Institute et al., 2022).

For the difference in ages of the business owners, older business owners usually have more extensive and established professional networks. These networks can provide valuable business opportunities, mentorship, and resources that are essential for revenue growth and profitability.

Younger entrepreneurs often lack such networks, making it harder for them to find support and opportunities. Also, with more experience, older business owners are often better at managing risks. They have likely encountered various business cycles and challenges, giving them a better understanding of how to navigate uncertainties, including those related to digital finance adoption (Khursheed et al., 2022).

However, younger entrepreneurs are generally more familiar with the latest digital tools and technologies. Their comfort with technology can lead to more innovative and efficient business processes. They are quick to adopt digital finance tools, e-commerce platforms, and digital marketing strategies, which can streamline operations and reduce costs (Gao et al., 2023). Although digitalization offers substantial advantages in expanding UMSEs operations and accessing new markets, it also poses some challenges, notably in managing operational costs in the early stage. Consequently, UMSEs must adeptly manage these dynamics, ensuring that the adoption of digital technologies aligns with their strategic objectives, enhances profitability, and supports long-term growth.

From a regional perspective, we find the stronger impact of financial digitalization on UMSEs performance outside Java-Bali regions. This has been attributed to several factors. First, the adoption of innovation typically follows an S-curve, with early adopters experiencing significant initial gains (Rogers, 2003). Off Java-Bali, which is less developed in terms of digital infrastructure, it is likely in the earlier stages of this curve. This means that the marginal gains from digitalization are likely higher in regions with less developed baseline infrastructure. Second, financial digitalization can offer significant efficiency gains and competitive advantages in these settings. The relatively lower competition in areas off Java-Bali allows these businesses to realize more substantial benefits from digitalization. Third, UMSEs in off-Java-Bali regions may exhibit greater flexibility and adaptability in their operational models. The need to overcome more significant logistical and infrastructural challenges can foster a more resilient and innovative business culture, so the latter regions may be better positioned to leverage the benefits of digital financial tools (McKinsey & Company, 2020).

5. Conclusion

The COVID-19 pandemic and the associated mobility restrictions have induced many UMSEs to move online and utilize digital finance to survive and thrive in the post-pandemic era. Financial digitalization includes a diverse array of financial offerings, such as digital banks, fintech loans, and mobile payment, aiming to make financial services accessible to a broader population segment. Using field survey data from Indonesia, we investigate the impact of this financial digitalization of UMSEs on their business performance and business innovation.

We find that, in terms of business performance, financial digitalization increases UMSEs' revenue per worker (a proxy for productivity), revenue growth, and the number of employees. However, it also increases the cost per worker, resulting in a neutral effect on profit per worker. Meanwhile, in terms of business innovation, financial digitalization increases UMSEs' probability of having out-of-town customers, the proportion of those out-of-town customers, the likelihood of engaging in exporting activities, and product diversification.

Results from heterogeneity analysis indicate that the impact of financial digitalization on business performance and business innovation is similar for both male and female-owned UMSEs. However, older enterprise owners seem to benefit more from financial digitalization on business performance, while for younger entrepreneurs, financial digitalization leads to stronger business innovation. Finally, across locations, the impact of financial digitalization on business performance indicators is more discernible outside Java-Bali Island, while the effects on business innovation indicators are stronger in Java-Bali Island, in particular on the likelihood of export.

The findings show that while financial digitalization offers substantial advantages in expanding UMSEs operations and accessing new markets, it also introduces challenges in managing operational costs. This implies that policy needs to be directed to assist UMSEs in ensuring that adopting digital technologies aligns with their strategic goals and contributes positively to overall profitability.

Overall, the findings indicate that advancing financial digitalization for UMSEs in developing countries necessitates a multi-faceted approach. The focus should be on enhancing digital and financial literacy to help enterprise owners manage digital transaction costs. Governments and financial institutions should also work to reduce these costs and offer low-interest loans for digital connectivity. Upgrading digital infrastructure in underserved regions will help UMSEs effectively use digital financial services, hence broadening their market reach and improving their productivity. Establishing regulatory sandboxes and enhancing cybersecurity will foster innovation and protect against digital threats. Additionally, ensuring consumer protection safeguards data privacy and financial interests while maintaining transparency and fairness is deemed necessary for the digital ecosystem to evolve.

These measures accelerate financial digitalization for UMSEs while providing financial system stability and security. Continuously monitoring and evaluating the impact of digital finance on UMSEs will help refine and enhance the effectiveness of these initiatives, ensuring that the sector not only adapts to but thrives in the evolving digital economy. This integrated strategy will provide UMSEs with the tools necessary to expand operationally and competitively, both locally and internationally, fostering inclusive and sustainable economic growth.

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Appendix

Table A1. Summary statistics (all observations)

Variable	Obs	Definition	Mean	SD
Outcome Variable				
Revenue per worker (Logarithm scale)	5,035	The UMSEs' sales per worker	15.365	1.089
Cost per worker (Logarithm scale)	5,035	The UMSEs' cost per worker	14.575	1.118
Profit per worker (Logarithm scale)	5,033	The UMSEs' profit per worker	14.672	1.145
Sales growth	5,035	The UMSEs' annual sales growth	0.193	0.152
Number of employees				
No employee	5,035	= 1 if the UMSE has no employee, 0 otherwise	0.619	0.486
1-5 employees	5,035	= 1 if the UMSE has 1-5 employees, 0 otherwise	0.290	0.454
6-10 employees	5,035	= 1 if the UMSE has 6-10 employees, 0 otherwise	0.070	0.255
> 10 employees	5,035	= 1 if the UMSE has > 10 employees 0 otherwise	0.021	0.144
Out-of-Town customers	5,035	= 1 if the UMSE have out-of-town customers, 0 otherwise	0.289	0.453
Percentage of Out-of-Town Customers to Total Customers	5,035	The percentage of out-of-town customers to the total customers	8.704	18.460
Export dummy	5,035	= 1 if the UMSE exports their products, 0 otherwise	0.012	0.108
Diversification	5,035	= 1 if the UMSE does a diversification when a business shock comes, 0 otherwise	0.225	0.418
Treatment Variable				
Digital Finance	5,035	= 1 if the UMSE is equipped with digital banks, e-wallet (e-payment), and online lending (P2P/fintech), 0 if only using conventional finance services	0.647	0.478
Education				
No school/elementary school	5,035	= 1 if the UMSE's owner has not attended school or attained elementary school, 0 otherwise	0.024	0.153
Junior high school	5,035	= 1 if the UMSE's owner attained junior high school, 0 otherwise	0.050	0.219
Senior high school	5,035	= 1 if the UMSE's owner attained senior high school, 0 otherwise	0.534	0.499
Undergraduate/diploma	5,035	= 1 if the UMSE's owner attained an undergraduate/diploma degree, 0 otherwise	0.372	0.483
Graduate/doctoral	5,035	= 1 if the UMSE's owner attained a graduate/doctoral degree, 0 otherwise	0.019	0.138
SME's Characteristics				
Sector	5,035	= 1 if the UMSE operates in the agriculture sector, 0 otherwise (industry/service)	0.044	0.206
Internet user	5,017	Percentage of internet users on the district's level	0.667	0.094
Online marketing	5,035	= 1 if the UMSE markets its product online, 0 otherwise	0.680	0.466
Firm's age	5,035	Age of the UMSE	6.810	5.837
Gender	5,035	= 1 if the UMSE's owner is male, 0 otherwise (female)	0.373	0.484
Age of owner	5,035	Age of the UMSE's owner	34.725	11.715

Internet speed	5,035	Average internet speed on the district's level	23.827	4.507
Java-Bali	5,035	= 1 if Java-Bali, 0 otherwise	0.773	0.419
Distance to nearest financial institution	5,035	Distance to the nearest financial institution (km)	0.630	0.483
Home-based business	5,035	= 1 if the UMSE is a home-based business, 0 otherwise	0.353	0.478
Surrounding entrepreneurship skill	5,035	= 1 if the UMSE is surrounded by well-skilled entrepreneurs, 0 otherwise	0.702	0.457
Number of BTS	5,035	Number of BTS on the district's level	341.083	212.904
Self-established business	5,035	= 1 if the UMSE is a self-established business, 0 otherwise	0.947	0.224

Table A2. Descriptive statistics of UMSEs using digital and not using digital finance

Variable	(1) Using digital finance	(2) Not using digital finance	(3) Mean difference (1) - (2)
Revenue per worker (Logarithm scale)	15.356	15.380	-0.024
Cost per worker (Logarithm scale)	14.730	14.640	-0.089
Profit per worker (Logarithm scale)	14.522	14.603	-0.080**
Sales growth	0.202	0.176	0.026***
Number of employees	2.662	1.830	0.832***
Out-of-Town customers	0.392	0.101	0.291***
Percentage of Out-of-Town Customers of Total Customers	11.955	2.735	9.220***
Export dummy	0.017	0.004	0.013***
Diversification	0.272	0.104	0.132***
Sector	0.045	0.042	0.003
No school/ elementary school	0.015	0.040	-0.025***
Junior high school	0.033	0.082	-0.049***
Senior high school	0.489	0.615	-0.126***
Undergraduate/Diploma	0.435	0.255	0.180***
Graduate/doctoral	0.026	0.006	0.020***
Internet user	0.667	0.667	0.000
Business License	0.431	0.296	0.134***
Firm's age	6.315	7.717	-1.401***
Gender	0.349	0.416	-0.066***
Age of owner	33.389	37.179	-3.789***
Internet speed (MBps)	23.791	23.894	-0.102
Java-Bali	0.804	0.715	0.089***
Distance to nearest financial institution	0.624	0.640	-0.016
Home-based business	0.306	0.341	-0.035
Surrounding's entrepreneurship skill	0.833	0.463	0.369***
Number of BTS per district	337.89	346.94	-9.05
Self-established business	0.949	0.944	0.005
Online Marketing	0.819	0.425	0.394***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The difference is measured by the two-sample *t-test with equal variances*

Table A3. Balance test

	Standardized differences		Variance ratio	
	Raw	Weighted	Raw	Weighted
Sector	0.017	-0.008	1.079	0.966
Education				
Junior high school	-0.212	-0.001	0.425	0.996
Senior high school	-0.255	0.031	1.057	0.997
Undergraduate/Diploma	0.388	-0.018	1.296	0.991
Graduate/doctoral	0.162	-0.045	4.221	0.749
Internet user	0.001	0.006	1.186	1.078
Business license	0.287	-0.016	1.180	0.993
Firm's age	-0.236	0.007	0.716	1.019
Gender	-0.140	-0.021	0.934	0.991
Age of owner	-0.326	0.016	0.837	0.978
Internet speed	-0.023	0.035	1.103	0.950
Island	0.214	-0.009	0.767	1.012
Distance to nearest financial institution	-0.034	0.006	1.019	0.997
Home-based business	0.040	-0.003	1.025	0.998
Surrounding's entrepreneurship skill	0.844	-0.004	0.558	1.004
Number of BTS	-0.042	0.030	1.233	1.232
Self-established business	0.021	-0.002	0.918	1.006
Number of employees				
1-5 employees	0.214	-0.002	1.243	0.998
6-10 employees	0.226	-0.058	2.406	0.835
> 10 employees	0.146	-0.015	3.241	0.908
Online Marketing	0.892	-0.004	0.607	1.003

	Mean of standardized differences	Mean of variance ratio
Raw	0,229	1.304
Weighted	0,015	0.986

Table A4. Overidentification test

Chi2	29.701
P-value	0.126

H0: Covariates are balanced:

Table A5. Baseline estimates using Augmented Inverse Probability Weighting (AIPW) of multi-valued treatment effects

	Business Performance				Business Innovation				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial Digitalization	0.093^{***}	0.185^{***}	0.031	0.017^{***}	0.484^{***}	0.164^{***}	0.056^{***}	0.008^{***}	0.053^{***}
	(0.036)	(0.038)	(0.038)	(0.005)	(0.080)	(0.014)	(0.005)	(0.002)	(0.014)
Observation	5,017	5,017	5,016	5,017	5,017	5,017	5,017	5,017	5,017

Note: (1) Revenue per worker, (2) Cost per worker, (3) Profit per worker, (4) Annual sales growth, (5) Number of employees: No employee, 1-5 employees. 6-10 employees, > 10 employees, (6) Dummy of having out-of-town customers, (7) Percentage of out-of-town customers to the total customers, (8) Dummy of exporting products, (9) Diversification.

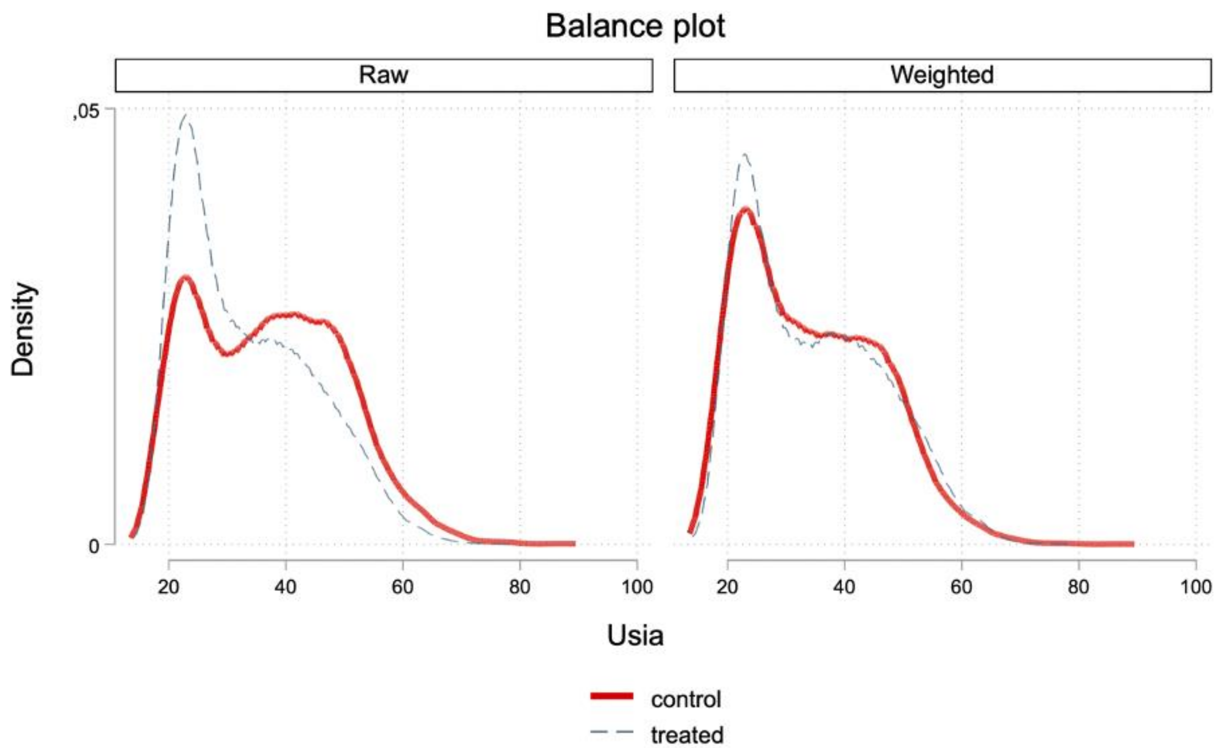
Table A6. Baseline estimates using Inverse Probability Weighting (IPW) of multi-valued treatment effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial Digitalization	0.104***	0.197***	0.042	0.016***	0.456***	0.159***	0.054***	0.008***	0.053***
	(0.039)	(0.042)	(0.035)	(0.005)	(0.087)	(0.015)	(0.005)	(0.002)	(0.015)
Observation	5,017	5,017	5,016	5,017	5,017	5,017	5,017	5,017	5,017

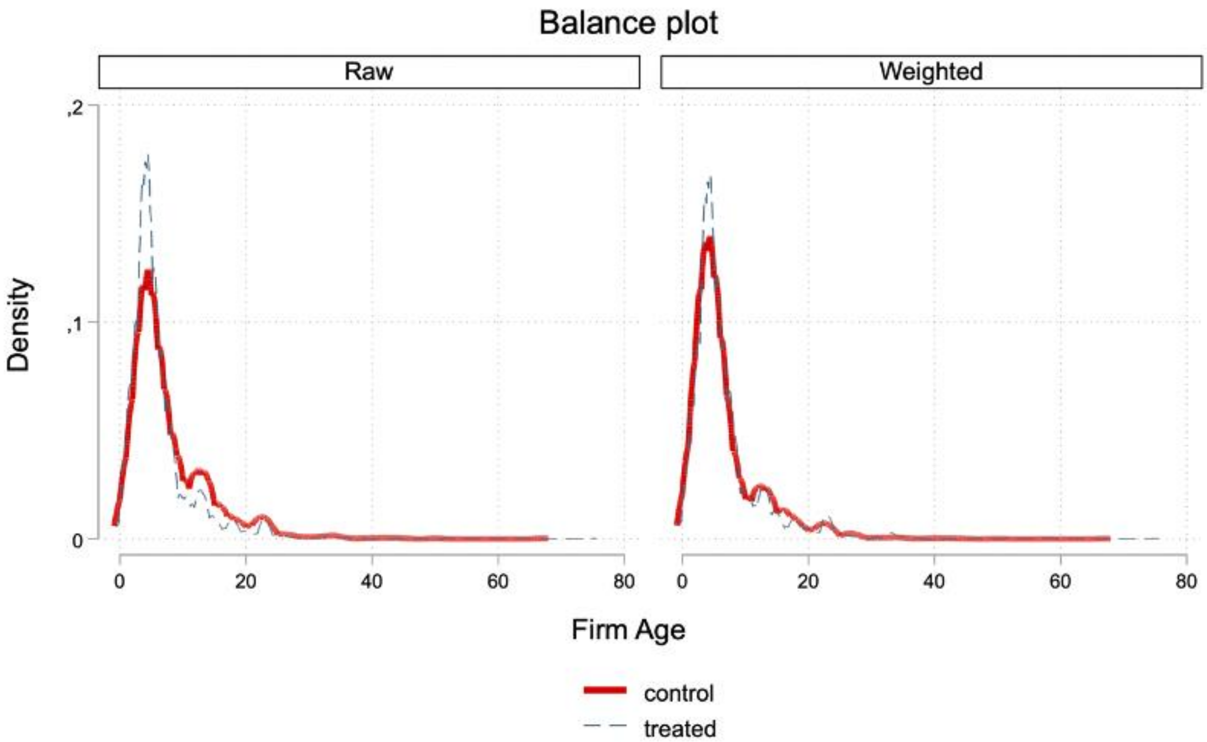
Note: (1) Revenue per worker, (2) Cost per worker, (3) Profit per worker, (4) Annual sales growth, (5) Number of employees: No employee, 1-5 employees. 6-10 employees, > 10 employees, (6) Dummy of having out-of-town customers, (7) Percentage of out-of-town customers to the total customers, (8) Dummy of exporting products, (9) Diversification.

Figure A1. Balance plot

(a) Balance plot of owner’s age



(b) Balance plot of firm age



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Policy Perspectives

PP/25-02

Powering Payments: The Role of Technology in ASEAN's Regional Payment Connectivity Initiative

June 2025

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Powering Payments: The Role of Technology in ASEAN's Regional Payment Connectivity Initiative

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June 2025

Abstract

Technological innovation has played a pivotal role in enhancing regional payment connectivity. Specifically, technological advancements in cross-border transaction system have improved operational efficiency, while enhancing security, transparency, and trust across diverse financial networks. These developments have been central to the establishment of the ASEAN RPC, paving the way for greater financial inclusion and economic development in the region. Although regulatory and governance hurdles remain, they can be addressed through coordinated efforts that integrate sound policy framework and innovative technology.

This study examines the role of technological advancements in driving the progress and recent expansion of the RPC. It focuses on key initiatives underpinning its development and benchmarks them against similar cross-border payment initiatives worldwide. Through this comparative analysis, the study highlights both the strengths and limitations of innovative technologies in addressing existing challenges, improving payment systems and identifying potential areas for further enhancement. The study also aims to provide recommendations to strengthen and refine the RPC moving forward.

JEL classification: F15, F36, G21, L86, O33

Keywords: ASEAN Regional Payment Connectivity; Cross-border payments; Fast Payment Systems; Financial integration; ISO 20022; API; Financial inclusion; Real-Time Gross Settlement

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Abbreviations

ADB	Asian Development Bank
AEC	ASEAN Economic Community
AI	Artificial Intelligence
AFAQ	Arabian Gulf System for Financial Automated Quick Payment Transfer
AML	Anti-Money Laundering
AMRO	ASEAN+3 Macroeconomic Research Office
API	Application Programming Interface
ARPCSO	Arab Regional Payments Clearing and Settlement Organization
ASEAN	Association of Southeast Asian Nations
BAC	Business Advisory Council
BIS	Bank for International Settlements
BISIH	BIS Innovation Hub
BoK	Bank of Korea
BoT	Bank of Thailand
BSP	Bangko Sentral ng Pilipinas
BNM	Bank Negara Malaysia
CBDC	Central Bank Digital Currency
CDD	Customer Due Diligence
CMIM	Chiang Mai Initiative Multilateralization
CPMI	Committee on Payments and Market Infrastructures
DLT	Distributed Ledger Technology
DEFA	Digital Economy Framework Agreement
ECB	European Central Bank
EU	European Union
FATF	Financial Action Task Force
FPS	Fast Payment System
FSB	Financial Stability Board
FX	Foreign Exchange
GCC	Gulf Cooperation Council
IBAN	International Bank Account Number
ICT	Information and Communications Technology
ISO	International Organization for Standardization
ITA	International Trade Administration
KYC	Know Your Customer
MAS	Monetary Authority of Singapore
ML	Machine Learning
MoU	Memorandum of Understanding
MSME	Micro, Small, and Medium Enterprise

PAPSS	Pan-African Payment and Settlement System
PPP	Public-Private Partnership
QR	Quick Response (code)
RBI	Reserve Bank of India
RBA	Reserve Bank of Australia
RPC	Regional Payment Connectivity
RTGS	Real-Time Gross Settlement
SARB	South African Reserve Bank
SECMCA	Central American Monetary Council

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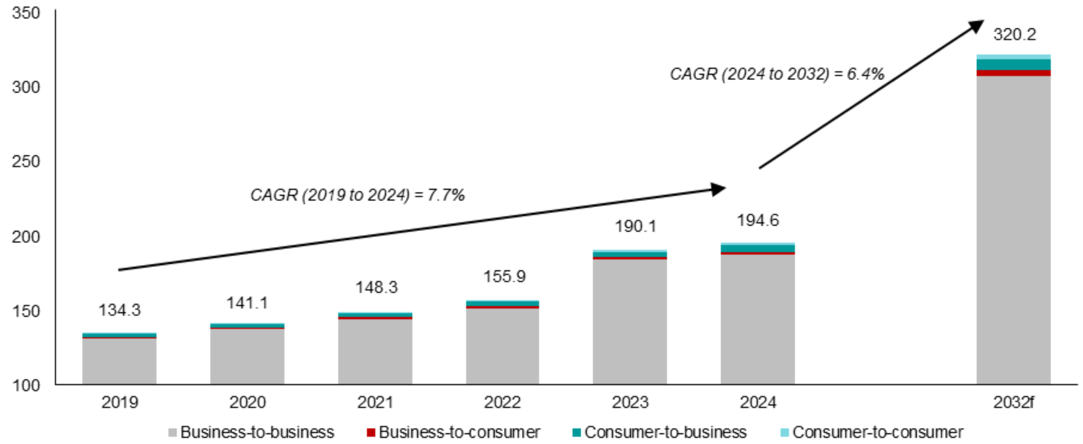
I. Introduction

1. The global payments landscape has changed significantly over the past decade due to technological advancements. Cross-border payments have historically been processed through a chain of correspondent banks for wholesale payments and through closed-loop systems (i.e. a single platform connecting both the payee and the payer) for retail payments. These led to long transaction chains, fragmented and truncated payments data, high capital costs and weak competition causing high costs, low speed, limited access, and insufficient transparency (BIS 2022). The advent of new technology (such as APIs and cloud computing) and messaging standards have provided a solution to these long-standing issues by facilitating the interoperability of various payment systems. As a result, technology has been an enabler for a significant rise in cross-border payments across the world (Figure 1).

Figure 1. Global Market Size and Growth in Cross-border Payments (In USD trillion)



Sources: Ernst & Young LLP 2024; FXC Intelligence 2025.
Note: Business-to-business segment includes wholesale payments. CAGR = compound annual growth rate. f = forecast

2. While the rise has been enabled by technological innovations, the public sector—comprising central banks, regulatory authorities, and international organizations, has played a vital role in driving progress. These entities are collaborating to harmonize regulatory frameworks, develop cross-border payment infrastructure, and implement robust data protection laws. Key global initiatives include the G20's cross border payments roadmap (FSB 2024), the Financial Action Task Force (FATF) guidelines for anti-money laundering and combat the financing of terrorism (AML/CFT) compliance (FATF 2017), and ISO 20022 adoption by various country authorities. The authorities and international bodies have strengthened AML/CFT regulations and their enforcement to ensure integrity of transactions. Several authorities have promoted innovation, development, and interoperability in payment systems, mostly in conjunction with the private sector. Various bilateral and multilateral initiatives, such as ASEAN's Regional Payment Connectivity (RPC), have also played a vital role in reflecting the commitment and encouraging cross-border payment linkages.

3. ASEAN's RPC initiative represents a significant step toward formalizing the region's commitment to enhancing the intra-region payment network. This paper aims to take stock of the developments, compare it with other similar payment initiatives, and identify potential areas for further enhancement. The paper is structured as follows. Section II provides an overview and key development milestones of the ASEAN RPC. Section III discusses the role of technology in enabling cross-border payment connectivity, not only in ASEAN RPC but also other such initiatives across the world. Section IV examines and compares the policy objectives and structures of various payment connectivity initiatives across the world while Section V lists the challenges in enabling the connectivity and mechanisms employed to achieve integration. Section VI concludes with discussing policy considerations and the way forward for the ASEAN RPC.

II. Overview of ASEAN Regional Payment Connectivity

4. In November 2022, ASEAN-5 member states—namely Indonesia, Malaysia, the Philippines, Singapore, and Thailand—signed the Memorandum of Understanding (MoU) on Cooperation on Regional Payment Connectivity (RPC) at the sidelines of the G20 Leaders' Summit in Bali. This landmark initiative aims to strengthen bilateral and multilateral payment connectivity to promote faster, cheaper, more transparent, more inclusive cross-border payments in the region. Since its inception, the initiative has expanded to include Vietnam (25 August 2023), Brunei (29 February 2024), Lao PDR (3 April 2024) and Cambodia (8 April 2025), bringing the total number of ASEAN participants to nine.[3] Payment linkages are being developed with non-ASEAN economies, such as Hong Kong, India, and Japan.[4] [5]

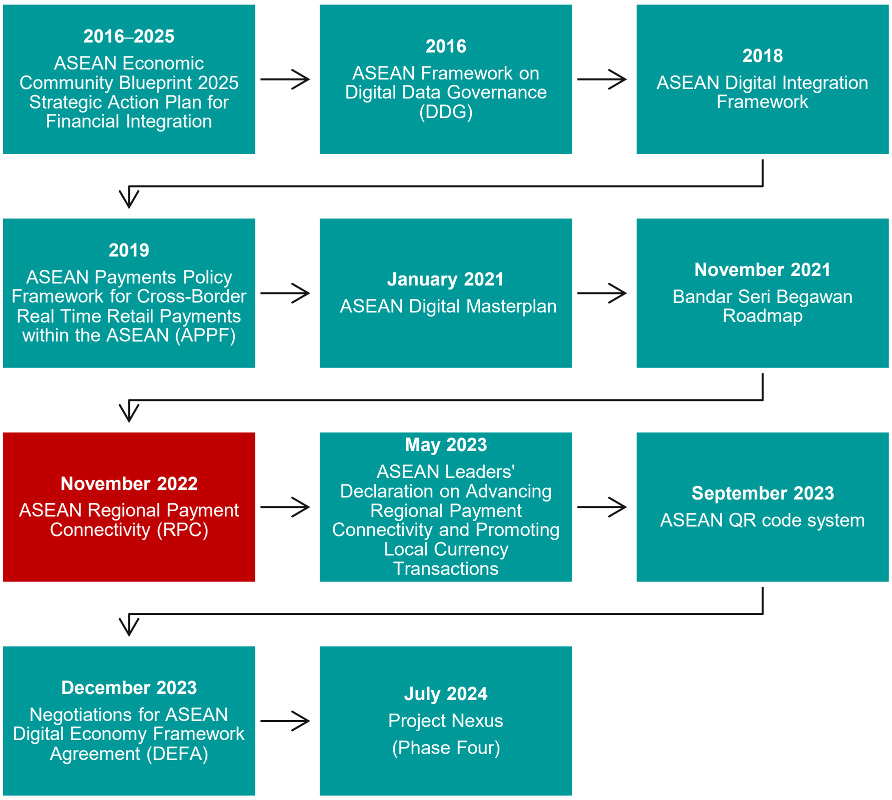
5. The RPC aligned with the objectives set out by ASEAN and G20 targets on payment connectivity. The initiative aims to strengthen and enhance cooperation on payment connectivity through the development of faster, cheaper, more transparent, and more inclusive cross-border payments which aligns with the shared vision for greater regional economic integration, including payment and settlement systems, under the ASEAN Economic Community Blueprint (AEC) 2025. The initiative is also in line with Indonesia's 2022 G20 Presidency priority agenda in digital transformation and supports the targets set at the global G20 Roadmap for Enhancing Cross-Border Payments.

6. The initiative aims to modernize payments infrastructure while strengthening intra-region economic ties. Built on the ASEAN Payments Policy Framework for Cross-Border Real Time Retail Payments Within the ASEAN Region, the RPC cooperation encompasses several modalities, including Quick response (QR) code-based and real-time cross-border payments. According to various central bank press releases (BNM 2022, BOL 2024, BOT 2022, and MAS 2023), the goal of the RPC is to modernize payments infrastructure and make inter-country transactions more seamless, convenient, and

3 For brevity, "Brunei Darussalam" is referred to as "Brunei" in the text.
4 For brevity, "Hong Kong, China" is referred to as "Hong Kong" in the text.
5 On 4 December 2023, the Hong Kong Monetary Authority (HKMA) and the Bank of Thailand (BOT) launched the FPS x PromptPay Link to enable cross-border QR code payment interoperability between Hong Kong and Thailand. Singapore successfully linked its PayNow system with India's Unified Payments Interface (UPI) on 21 February 2023 while the South Asian nation officially joined Project Nexus in June 2024 to enhance its cross-border payment capabilities with the ASEAN region. Meanwhile, Japan's Ministry of Economy, Trade and Industry (METI) has announced that the country would implement cross-border QR code payment interoperability with ASEAN by 2025.

affordable, allowing individuals and businesses, particularly micro, small and medium enterprises (MSMEs), to conduct transactions across the ASEAN region with ease, hence promoting trade, investment, remittances and people mobility. In parallel, authorities are working to harmonize and standardize payment systems across the region, in particular the use of proxy identifiers and the adoption of ISO 20022.[6] Furthermore, the RPC compliments ongoing efforts to promote the use of local currency for cross-border settlement in the region. With this, the RPC has been further enhanced as an additional avenue for deepening financial integration through promoting local currency usage.

Figure 2. ASEAN: Timeline of Initiatives on Cross-Border Digital Payment Connectivity



Source: AMRO staff compilation.
Note: The timeline refers to the initiation or launch dates of the respective initiatives.

7. **Prior to the launch of the RPC, ASEAN had already undertaken several foundational efforts to strengthen digital payment connectivity (Figure 2).** These include the ASEAN Economic Community (AEC) 2025 Strategic Action Plan for Financial Integration (2016–2025) which focused on liberalizing banking, insurance, and capital markets. The ASEAN Framework on Digital Data Governance in 2018 advanced previous efforts on data protection framework and a guidance on cross-border data flows, taking into accounts varying level of development and readiness across member states (TELMIN 2012). To harness the potential of digital integration in boosting the regional economy and competitiveness, ASEAN members have developed various frameworks, including the

[6] According to its official definition, ISO 20022 is a single standardization approach (methodology, process, repository) to be used by all financial standards initiatives. Also see Box 2 for more information.

ASEAN Digital Integration Framework (ASEAN 2018) to identify priority areas for deliberate policy actions and the ASEAN Payments Policy Framework for Cross-Border Real Time Retail Payments within the ASEAN Region (ASEAN 2019) to provide specific guiding principles for the implementation of cross-border, instant retail payments and promote interoperability between the payment rails.

8. **ASEAN's shift toward digitalization accelerated significantly during the COVID-19 pandemic, as digital technology became vital for maintaining the continuity of education, business, industry, and government amid lockdowns and restrictions**. In response, the region adopted the ASEAN Digital Masterplan 2025 in January 2021, followed by the Bandar Seri Begawan Roadmap in October 2021—both aimed at deepening digital transformation and supporting regional economic recovery (ASEAN Secretariat 2021a and 2021b). These foundational initiatives paved the way for the development of the Digital Economy Framework Agreement (DEFA) (ASEAN Secretariat 2023a). A comprehensive study was commissioned in 2023 to gather private sector perspectives and support the formulation the DEFA's roadmap (ASEAN Secretariat 2023b). The aim of the agreement is to forge stronger digital ties among members and to enable businesses to capitalize on the exponential growth in ASEAN's digital economy. According to the study, the digital economy is projected to expand from approximately USD300 billion in 2023 to USD1 trillion by 2030 through natural adoption of digital technologies but progressive rules in DEFA could accelerate the growth and expand the digital economy further to almost USD2 trillion by 2030. In this regard, the provision of more efficient and more inclusive payment channels under the RPC complements the goals of DEFA. Negotiations on DEFA[7] between ASEAN member states began in September 2023, with a target to conclude agreements by the end of 2025.

9. **At the same time, the vision of having an ASEAN Interoperable QR code payment standard remains intact**, especially with many bilateral cross-border QR code payment linkages being launched in the last few years. To date, the payment system of seven ASEAN economies, namely Cambodia, Indonesia, Lao PDR, Malaysia, Singapore, Thailand and Vietnam, have been connected through these bilateral QR payment linkages as well as linking fast payment systems (Figure 3). These initiatives will lower transaction costs and minimize foreign exchange risks, aligning the objectives of the RPC (Lukiman and others 2023).

[7] The DEFA negotiations are based on nine elements under four objectives. The elements and objectives include 1) facilitating "digital trade" with electronic documents and interoperable processes; 2) creating efficient cross-border e-commerce (both under the objective of accelerating growth); 3) promoting digital payments and electronic invoicing; 4) developing mutually recognizable and interoperable digital identity and electronic authentication framework (both under the objective of driving interoperability across ASEAN); 5) protect data privacy while facilitating cross-border data flow; 6) improve cooperation in cybersecurity and comprehensive protection to parties (both under the objective of ensuring responsible digital growth); 7) establishing mechanisms for regulatory cooperation; 8) facilitate digital talent mobility; 9) create a transparent competitive environment with better choice for consumers (all three under the objective of strengthening cooperation between nations).

Figure 3. ASEAN+3: Selected Cross-border Payment Linkages, Stylized

Economies	Project/ Network name	Launch Date
Japan–Thailand	MyPromptQR at merchants in Japan	December 2018
Cambodia–Thailand	Thai QR–KHQR	February 2020
Thailand–Vietnam	Thai QR–VietQR	March 2021
Singapore–Thailand	PromptPay–PayNow	April 2021
Malaysia–Thailand	DuitNow QR–Thai QR	June 2021
Indonesia–Thailand	Thai QR–QRIS	August 2021
Singapore–Thailand	NETS (QR)–Thai QR	September 2021
Indonesia–Malaysia	QRIS–DuitNow (QR)	January 2022
Malaysia–Singapore	DuitNow (QR)–NETS (QR)	March 2023
Cambodia–Lao PDR	KHQR–LAOQR	August 2023
Indonesia–Singapore	QRIS–NETS (QR)	November 2023
Malaysia–Singapore	DuitNow–PayNow	November 2023
Cambodia–Vietnam	KHQR–VietQR	December 2023
Hong Kong–Thailand	FPS QR–Thai QR	December 2023
Thailand–Lao PDR	Thai QR–LAOQR	April 2024
Cambodia–Korea	Jeonbuk Bank payment via KHQR in Cambodia	September 2024
Cambodia–Malaysia	DuitNow - KHQR	September 2024
Cambodia–Private Network*	KHQR–12 international payment users via AliPay+*	October 2024
Cambodia–Vietnam	KHQR/Bakong–VietQR	October 2024
Lao PDR–Vietnam	Cross-border payment using Lao QR code	January 2025

Source: AMRO staff compilations.
Note: The boundaries and any other information shown on the map do not imply, on the part of AMRO, any judgment on the legal status of any territory or any endorsement or acceptance of such boundaries. Cross-border payment linkages enable efficient and real-time cross-border fund transfers, usually in small amounts, among participating members. The table aims to list selected linkages and is not exhaustive. Other planned initiatives are the cross-border payment linkages between the Philippines and Singapore, and between Cambodia and Thailand. There is a wide range of FinTech products of varying scales connecting e-wallet platforms across economies that are not listed.
* Cambodia—AliPay+ linkage allows users to make cross-border QR payments to vendors using KHQR from their partner digital wallets in China, Hong Kong (China), Malaysia, the Philippines, Korea, and Singapore, as well as in Mongolia, Macao (China), and Italy.

10. The developments of the RPC have attracted interest by International Organizations as well as countries outside the ASEAN. Based on the success of bilateral payment linkages by ASEAN economies, such as PromptPay-PayNow (PPPN), the Bank for International Settlements Innovation Hub (BISIH) initiated Project Nexus, which explored the possibility transforming connectivity model from bilateral to multilateral (BISIH 2021). Since its inception in 2022, the BISIH has worked with the regulators from Indonesia, Malaysia, the Philippines, Singapore, Thailand, and India (BISIH and others 2024a) (Box 1). The project also gathered insights from international experience and has scaled up to include more global participation. For example, the Eurosystem's TARGET Instant Payment Settlement (TIPS) system was included in the project's proof-of-concept in 2022 (BISIH and others 2024a) and the European Central Bank also announced its intention to join as a special observer in Nexus, further expanding the project's reach.

Box 1. Multilateral Cross-border Payment Linkage: Project Nexus

Although bilateral connections between domestic fast payment systems (FPS) have demonstrated the potential to enable near-instant cross-border transfers, scaling such arrangements becomes significantly complex as more countries are involved. Each additional connection requires extensive legal, technical, and operational negotiations, creating a costly and unsustainable model for broader regional or global interoperability. This high cost also discourages the development of linkages to smaller economies.

To tackle this challenge, central banks and international organizations have explored multilateral approaches. One prominent initiative is Project Nexus, a hub-and-spoke platform designed to connect multiple FPS through a single hub, thereby simplifying and accelerating cross-border payments across jurisdictions. Project Nexus was initiated by the Bank for International Settlements Innovation Hub (BISIH) with a coalition of central banks and payment authorities. The concept was first explored in 2021 by the BISIH in collaboration with the Monetary Authority of Singapore (MAS) and the National Payments Corporation of India (2021). In 2022, a working prototype was established to connect the test systems between Europe's TIPS, Malaysia's Real-time Retail Payments Platform, and Singapore's Fast and Secure Transfers systems (BISIH 2023). A comprehensive blueprint of the project was completed in July 2024, outlining the governance, scheme, and oversight arrangements, business and revenue model, as well as Nexus' technology architecture and operational model. Subsequently, in March 2025, central banks from Malaysia, the Philippines, Thailand, Singapore, and India have formally established a multilateral not-for-profit organization, Nexus Global Payments, to manage the development and operations of Nexus.

Project Nexus works by establishing a hub-and-spoke multilateral network connector, or Nexus Gateway. The Nexus Gateway is an infrastructure that manages cross-border communication between domestic FPS and coordinates the processing of Nexus payments between countries. This model reduces the need for bespoke bilateral connections by allowing each system to connect once to the hub rather than multiple times to other systems. The system also leverages the domestic proxy directories of the FPS operators (which, for example, maps phone numbers to bank accounts across jurisdictions) through a lookup service to facilitate cross-border fund transfers. It also prescribes a harmonized set of rules and standards for message formats and foreign exchange provider connections to establish the connections. In addition, by lowering the participation barrier, Nexus allows new economies to join the platform without disrupting existing links, and the model is being developed to be interoperable with other cross-border initiatives.

As regional economies continue to embrace digital financial infrastructure, initiatives like Nexus exemplify the potential of collaborative innovation in achieving the G20's targets for faster, cheaper, more inclusive, and transparent cross-border payments.

III. Technological Enablers in Cross-border Payment Connectivity Initiatives

11. Around the world, regional payment initiatives share some common objectives, include enhancing payment efficiency, reducing costs, and supporting economic and financial integration. By leveraging technological advancements and multilateral collaboration, these initiatives provide a regional alternative to correspondent banking networks, facilitating faster, cheaper, and more transparent payments (Table 1). They also seek to strengthen the use of local currencies and promote financial inclusion. These initiatives were developed by enhancing existing systems or by establishing new regional connectivity infrastructure. Nonetheless, all initiatives seek interoperability and connectivity between payment systems of different countries.

12. Multiple successful regional and global payment initiatives have leveraged various technological advancements and standardizations. These include TIPS in Europe, the Pan-African Payment and Settlement System in Africa, the Arabian Gulf System for Financial Automated Quick Payment Transfer of the Gulf Cooperation Council, the Interconnected System of Payments in Central America (SIP), and various bilateral linkages (both within and outside ASEAN) between domestic payment systems. A common thread across these initiatives is the employment of one or more innovative technologies, such as real-time gross settlement (RTGS), fast payment systems (FPS), Application Programming Interface (API), and Cloud Computing. The deployment of international standards—particularly the ISO 20022—has played a crucial role in enabling system compatibility and message harmonization (Box 2). Intensified global policy directives towards financial digitalization also played a catalytic role in the technological adoption of cross-border payment initiatives.

Box 2. The Adoption of ISO 20022

Cross-border payment data was historically exchanged via SWIFT message type (MT) messaging standard; however, it lacked interoperability with domestic payment systems, which varied across economies, causing delays and adding operational challenges. Indeed, the Group of Twenty (G20)[1] has identified that differences in messaging standards between the domestic payment systems and cross-border payments as a major friction in improving cross-border payments (FSB 2022). The SWIFT MT standard, which was formatted according to ISO 15022, also does not support the exchange of necessary information, such as compliance reporting or end-to-end payment transparency, adversely affecting automation efforts.

ISO 20022, introduced in the mid-2000s and expected to fully replace ISO 15022, is an international standard for electronic data exchange between financial institutions. The standard offers a common framework for developing financial messages using a structured, XML-based syntax that enhances interoperability and data richness. For example, ISO 20022 can include up to 940 data elements for a customer credit transfer message,[2] while ISO 15022 messages for customer credit transfers includes around 23 fields (Parmar 2023 and iotafinance.com). By improving data richness, ISO 20022 improves interoperability, automation, compliance, and fraud detection. Its adoption increases the speed, transparency, and efficiency of the payments. SWIFT acknowledged the benefits of ISO 20022 and started migration in March 2023, with a coexistence phase until November 2025.

1/ G20 comprises 19 major advanced and emerging economies, the African Union and the European Union. The member economies are Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Korea, Mexico, Russia, Saudi Arabia, South Africa, Türkiye, the United Kingdom, and the United States.

2/ See ISO 20022 Message Definitions for a full list of available data fields

13. The developments in real-time payment systems enable the establishment of regional payment connectivity. The two most common systems are the RTGS and FPS. RTGS systems process and settle high-value transactions instantly on a per-transaction basis, reducing settlement risks and enhancing liquidity management. FPS, unlike RTGS, target high-volume, low-value instant or near-instant transactions, fostering financial inclusion and economic participation. Both systems can be linked between economies to facilitate multilateral cross-border payments (Table 1). The Committee on Payments and Market Infrastructures (CPMI) (BIS 2022) suggested four thematic interlinking models (Figure 4):

- **Single Access Point Model:** Participants in one domestic payment system access a foreign system through a single entity that directly participates in the foreign system.

- **Bilateral Link Model:** Participants in a domestic system can directly reach all participants in a foreign system via a bilateral link, eliminating the need for a single gateway entity.

- **Hub and Spoke Model:** Multiple payment systems (the spokes) connect to a common intermediary (the hub), facilitating transactions among them.

- **Common Platform Model:** Participants from different jurisdictions interact on a single, integrated technical platform, allowing direct cross-border transactions.

14. At the same time, the development of APIs has played a critical role in enabling the integration of multilateral payment systems. An API is a software application that establish machine-to-machine linkages between systems at financial institutions. They facilitate seamless data exchange, system interoperability, and real-time transactions between infrastructure at banks, FinTechs, and other financial institutions.[8] A survey by the CPMI (BIS 2024b) showed that 93 percent of FPS and 65 percent of RTGS systems have been using or have plans to use API within the next five years.

15. However, APIs developed by different participants may lack a general standardization, making them incompatible. Between economies, API development is subjected to different jurisdictions and regulations, resulting in different formats. Similarly, differences in the industries, i.e. financial institutions vis-à-vis nonbank financial institutions or FinTechs, different business use cases, or competition between market participants may also result in fragmented designs of API.[9] This fragmentation of API technical standards hinders their potential in cross-border payments. Since 2023, the Financial Stability Board

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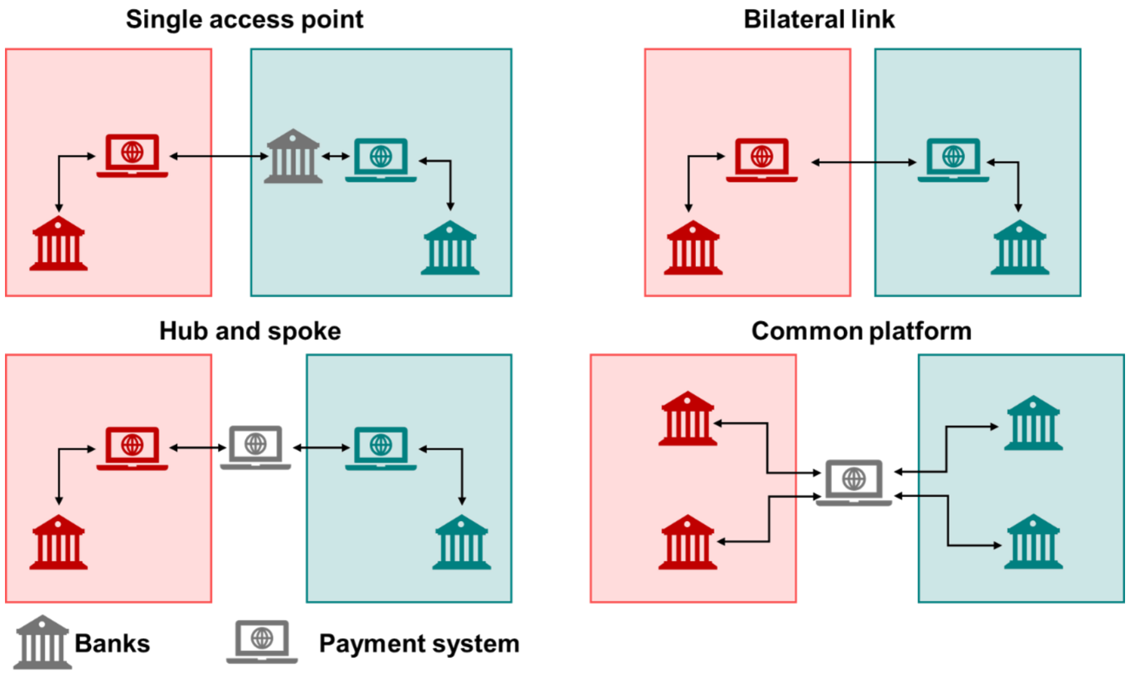
[8] An API provides a means for a software application to exchange data with other applications. In the context of cross-border payments, an API at a bank at a certain economy will allow another bank at a different economy to request and exchange information directly between the two applications. Once established, an API can be programmed to run automatically or to be embedded into a larger application serving the users. An API can also carry various security protocols and standards while limiting itself to a pre-determined data to both ensure the legitimacy of the sender as well contain the scope of the API. Because of that, APIs enable seamless and secure communication between banks, payment service providers, and FinTech platforms, which ultimately enable the possibility of real-time automation.

[9] A more detailed discussion regarding API development in financial institution can be found in BIS (2024b) and FSB (2023).

(FSB) has recommended for the harmonization of APIs for enhancing cross-border payments (FSB 2023).

16. **Successful multilateral payment initiatives would need to address the challenges of API fragmentation**. Regional cross-border payment initiatives have used APIs to link domestic payment systems across different jurisdictions—in bilateral linkage model—or create a standardized API framework for participants—in the hub-and-spoke and common platform models—ensuring seamless and real-time transactions despite regulatory and technical differences. For example, Singapore and India have utilized APIs to connect national fast payment systems, India's Unified Payments Interface (UPI), and Singapore's PayNow, enabling near real-time transfers between the two fast payment systems (BIS 2022). Similarly, PAPSS in Africa has integrated APIs to build connection with individual African central banks to support cross-border multi-currency transactions and allow financial institutions to process payments directly in local currencies without relying on correspondent banks (ITA 2022 and PAPSS).

Figure 4. Graphical Representation of Thematic Interlinking Model



Source: Adapted from BIS (2022)

Table 1. A Brief Summary of Selected Cross-border Payment Connectivity Initiatives

<table>
<tr><th>Initiative — Region (Year Established)</th><th>Interlinking Model</th><th>Description</th><th>Key Objectives</th><th>Enabling Systems and Focus</th><th>Connectivity Technology and Messaging Standard</th></tr>
<tr><td>ASEAN Regional Payment Connectivity (RPC) – ASEAN (2022)</td><td>Bilateral Link Model (with considerations for other modalities underway)</td><td>Within the RPC, bilateral payment linkages between national fast payment systems, such as PromptPay-PayNow, PromptPay-DuitNow, facilitating real-time cross-border payments using QR codes and instant payment networks.</td><td>• Promotes faster, cheaper, more transparent, and more inclusive cross-border payments
• Widens financial inclusion, especially for MSMEs
• Encourages the use of local currencies for cross-border transactions</td><td>• FPS linkages, QR cross-border payment linkages
• Retail payments</td><td>• Multiple bilateral linkages with API capabilities
• ISO 20022 (migration in progress)</td></tr>
<tr><td>TARGET Instant Payment Settlement (TIPS) – Eurozone (2018)*</td><td>Common Platform Model</td><td>TIPS is a pan-European instant payment system operated by the ECB, providing a single infrastructure that connects banks across the Eurozone for real-time settlements in central bank money, targeting retail payments.</td><td>• Enables payment service providers to offer fund transfers to their customers in real time using euro and Swedish kronor
• Ensure the whole of Europe enjoys instant payment services</td><td>• FPS
• Retail payments</td><td rowspan="2">• SWIFT messaging and SIA connection, with API capabilities
• ISO 20022</td></tr>
<tr><td>T2 – Eurozone (upgraded from TARGET2, launched in 2007) (2023)</td><td>Common Platform Model</td><td>T2 is the RTGS system for the Eurozone, handling high-value transactions and interbank settlements in central bank money within a unified infrastructure.</td><td>• Supports the implementation of the Eurosystem’s monetary policy and the functioning of the euro money market
• Minimizes systemic risk in the payments market
• Ensures the efficient processing of payments in euro</td><td>• RTGS
• Wholesale payments</td></tr>
<tr><td>Pan-African Payment and Settlement System (PAPSS) – Africa (2022)</td><td>Hub and Spoke Model</td><td>PAPSS serves as a centralized infrastructure that interconnects African central banks and financial institutions, streamlining intra-African transactions using local currencies.</td><td>• Enables the efficient flow of money securely across African borders, minimizing risk and contributing to financial integration across the regions
• Enhances intra-African trade by reducing reliance on foreign currencies, lowering transaction costs</td><td>• FPS and RTGS
• Retail & Wholesale payments</td><td>• Private network with API capabilities
• ISO 20022</td></tr>
</table>

Initiative — Region (Year Established)	Interlinking Model	Description	Key Objectives	Enabling Systems and Focus	Connectivity Technology and Messaging Standard
BUNA - Arab Regional Payment System – Middle East and North Africa (2020)	Common Platform Model	BUNA, operated by the Arab Monetary Fund, provides a unified cross-border payment platform for Arab countries and beyond, enabling real-time settlement in multiple currencies.	• Empowers Arab economies • Streamlines trade and relationships of the Arab countries with major partners • Facilitates financial inclusion and regional integration • Promote cross-border payments and making as efficient as domestic ones • Promotes usage of regional currencies • Strengthens compliance standards	• FPS and RTGS • Retail & Wholesale payments, Cross-border payments	• SWIFT messaging, API capabilities • ISO 20022
Arabian Gulf System for Financial Automated Quick (AFAQ) Payment Transfer RTGS – Gulf Cooperation Council (2016)	Common Platform Model	The AFAQ initiative interlinks GCC countries' RTGS systems, enabling high-value and cross-border transactions within the region, leveraging central bank infrastructure.	• Executes financial transactions in GCC local currencies on a real-time basis, with low fees, and within a safe, secure, and stable ecosystem	• RTGS • Wholesale payments	• Private network messaging with API capabilities • ISO 20022
Interconnected System of Payments (SIP) – Central America (2014)*	Hub and Spoke Model	SIP operates as a regional settlement hub for cross-border transactions between participating countries through SWIFT messaging.	• Promotes modernization of national payment systems • Contributes to the elimination of restrictions on cross border payments • Materializes the treaty on payment and settlement systems of Central America and Dominican Republic • Gives greater access to cross-border payment services • Compliments other regional initiatives regarding trade.	• RTGS • Wholesale payments	• SWIFT-based • ISO 20022 (planned adoption) (SECMCA 2022)

Sources: ASEAN Secretariat; TIPS; TARGET2; PAPSS; World Economic Forum; BUNA; Gulf Payments; Icon Solutions; and AMRO staff compilation.
Note: The table provides a summary of activities that have been completed as part of the initiative. Activities that are ongoing or planned for the future are not included.
Transaction values available for payment connections include TARGET Instant Payment Settlement (TIPS): USD 615 trillion in 2023 (ECB 2024); Pan-African Payment and Settlement System (PAPSS): USD 1 trillion in 2023 (Ecofin Agency 2024); and Interconnected System of Payments (SIP): USD 360 million in 2024 (Martinez 2025). According to estimates, USD 1.14 trillion of transactions were reported in the ASEAN's bilateral linkages (Twimbit 2025).

17. The adoption of ISO 20022 by institutions can offer a common standard for designing API for cross-border payments, promote interoperability of regional payment systems, and enable more efficient cross-border payments. By offering a consistent format for exchanging data and transaction information between financial systems, the standard fosters interoperability between different institutions and economies. In a study by the CPMI (BIS 2024c), 80 percent of the surveyed FPS and 88 percent of RTGS systems are expected to process ISO 20022 messages in the near future. Ten economies of the ASEAN region has also implemented the ISO 20022 to their FPS and all central banks of the region have either already adopted or are in process of adopting and implementing the standard to their RTGS systems (ABO 2023) (Table 2). By standardizing the information and form of data used across institutions, the ISO 20022 provides a standard for developers to ensure API interoperability, realising the full potential of digital connection.

Table 2. ASEAN: The Status of Implementing ISO 20022

Economy	RTGS	FPS
Brunei	Y	NA
Cambodia	Y	Y
Indonesia	E*	Y
Lao PDR	Y	NA
Malaysia	Y	Y
Myanmar	Y	NA
Philippines	Y	Y
Singapore	Y	Y
Thailand	Y	Y
Vietnam	E**	NA

18.

Sources: Asian Bond Online (2023); JICA and others (2018); and AMRO staff updates and compilation.
Note: As of February 2025. Y = ISO 20022 implemented; NA = not applicable or missing data; E = expected; RTGS = real-time gross settlement; FPS = fast payment systems.
* The RTGS system of Indonesia is expected to implement in 2027.
** Banks in Vietnam have been implementing ISO 20022 independently, but the standard has not been implemented systemwide.

19. The scalability and interoperability of cross-border payment systems can further benefit by the adoption of cloud computing. Cloud computing enables the delivery of computing services, such as servers, databases, networking, and analytics, using remote servers, allowing financial institutions to process transactions, manage payment gateways, and store financial data efficiently with minimal infrastructure set up. These features provide valuable opportunities for cross-border payment systems to support real-time transaction processing at reduced operational costs, enhanced system interoperability and scalability. Indeed, cloud computing has been used by financial institutions to enhance their operations and was used by BCS Financial Group to enable real-time cross-border payments between Singapore and India (Ping 2023).

20. In a cross-border payment system where transactions are being made seamlessly and almost instantly, additional technological solutions are needed to ensure compliance with AML/CFT and national regulations. Indeed, as cross-border transactions can be made near-real time, risks of payments being finalized before necessary compliance checks are completed emerge. As a solution, functioning regional connectivity initiatives implement real-time user screening to ensure compliance of these transactions, as used in the PPPN and UPI-PayNow systems (Baker McKenzie, MAS, and BoT 2022 and BIS 2022), apart from merely setting a cap to transaction. The system also needs to devise additional workflow to reject and manage the transactions in the event of a screening hit.

21. The increasing digitalization of cross-border payment systems and their payment data have opened new possibilities for advanced analytics using artificial intelligence (AI) and machine learning (ML). These technologies enable financial institutions to process large volumes of structured and unstructured data, facilitating real-time fraud detection, compliance monitoring, and risk assessment. For instance, AI and ML can identify anomalous transaction patterns indicative of fraudulent activities, thereby strengthening the security of cross-border payment systems (BCBS 2024). Moreover, the integration of AI/ML tools can improve the efficiency of payment processing by automating routine tasks and enabling predictive analytics for liquidity management. However, the adoption of these technologies also introduces challenges, including model risk, data bias, or new sources of cyber risk—attackers can use AI for fraudulent activities or submit corrupted data to misguide the AI (BIS 2024a). The implementation of AI/ML in cross-border payment systems requires careful consideration and robust oversight mechanisms.

22. Another transformative innovation is proxy mapping technology, which plays a vital role in making cross-border payments more accessible and inclusive. The use of proxy identifiers—also known as aliases—allows customers to replace technical bank details, such as the international bank account numbers (IBANs), with more familiar information, such as phone numbers, email addresses, and national identification numbers. Proxy identifiers help eliminate the need to share complex account information in cross-border payment, streamlining the payment process and significantly reducing the likelihood of errors and fraud. Proxy identifiers are managed in proxy data bases by the payment system operators, who also carry out necessary Know Your Customer (KYC) and AML/CFT checks, authenticity verification, and data storage. Recognizing the benefits of intuitive and user-friendly payment processes, regional payment initiatives across Europe, the Arab region, and ASEAN have widely adopted alias layers to enhance retail payment adoption. However, implementing alias systems across borders requires alignment in system design, such as differences in proxy lookup and proxy storage protocols, while also ensuring consumer protection through robust privacy safeguards and dispute resolution mechanisms, as discussed in the PPPN system (Baker McKenzie, MAS, and BoT 2022).

IV. Comparison of Various Payment Initiatives Across the World

23. Most payment interlinkages in emerging economies aim to promote more inclusive cross-border payments for the users. While the ASEAN RPC does not have an explicit set of objectives, it is understood from various central bank press releases of participating members that the initiative seeks to promote more inclusive cross-border payments for users, particularly for MSMEs (Table 1). The ADB estimated that such businesses accounted for 98.7 percent of total establishments in Asia. Additionally, MSMEs contribute 64.6 percent to employment, 38.3 percent to regional GDP, and 15.1 percent to exports in 2023 (ADB 2024). The importance of MSMEs underscores the need to expand essential financial services to the sector, enabling them to scale effectively and promote financial access and inclusion. In other emerging markets apart from the ASEAN economies, the mission to enhance financial inclusion through digital payment connectivity leverages on mobile and internet networks to bring small businesses online and enable access to financial services digitally.

24. Modernizing cross-border connectivity also enables cost-efficient and faster payments between users. By linking individual country payment systems with regional counterparts, it reduces the hassle for users to switch systems and currencies, while facilitating real-time, secure transactions at low costs. Indeed, payment linkages such as the PPPN reduced the transaction time from days to seconds, with significantly lower fees (Baker McKenzie, MAS, and BoT 2022). This reduction in friction eases the flow of money for businesses and consumers, who have traditionally faced higher costs when dealing with cross-border transactions and remittances. Indeed, one of the objectives for the RPC and other payment initiatives is to enhance efficiency in payments and transfers to strengthen intra-regional economic activities such as the transfer of remittances, trade transactions, and tourism.

25. Another common objective for payment initiatives is to promote the use of local currencies for payment settlements within a region. During the 42nd ASEAN Summit in 2023, leaders advocated for increased use of domestic currencies, which are linked to individual fast payment systems, to facilitate transactions through the ASEAN RPC. This aligns with the ASEAN Guideline on Local Currency Settlement Cooperation Framework (LCSF), which aims to promote local currency settlements, lower business costs, and reduce the reliance on the US dollar. Table 1 highlights that, in addition to the ASEAN, payment systems such as TIPS, PAPSS, and BUNA share a similar objective in enhancing the use of a common or local currency, or the currency of a regional counterpart, through digital payment connectivity.

26. Payment integrations outside of ASEAN include other objectives for idiosyncratic reasons and are enabled by the structures of the integrations. Most other integrations are for wholesale payments, which allows them to cater to objectives other than those of the ASEAN RPC. One objective of the eurozone's T2 network is supporting monetary policy and the functioning of money markets. According to the European Central Bank (ECB), T2 offers various features for efficient liquidity management, such as payment priorities, timed transactions, and liquidity reservation facilities. These tools help banks manage liquidity effectively, thus supporting the smooth functioning of money markets. T2 also helps to minimize systemic risk in the payments market by reducing the possibility of a single actor causing market collapse, thereby helping maintain financial stability. In the Middle East and North African region, the BUNA empowers the regional economies through improved financial infrastructure, while simultaneously strengthening compliance standards across the region. BUNA's infrastructure is built on microservices-based architecture with flexible APIs, allowing easy integration and real-time connectivity and supporting innovation in financial services (Ping 2024). According to BUNA, the system also operates under the framework of the Arab Regional Payments Clearing and Settlement Organization (ARPCSO), ensuring regulatory oversight and adherence to international principles for financial market infrastructures. Through the RPC, ASEAN participants also implicitly strive to meet some of these objectives by strengthening economic integration among member states and enhancing compliance frameworks including those for AML/CFT and ISO 20022 messaging standardization (MAS 2023). However, many objectives such as supporting monetary policy and money markets, efficient liquidity management, and providing improved and integrated financial infrastructure would need more cooperation amongst ASEAN participants.

27. While the various payment initiatives share similar objectives, we find that the structures of these initiatives and the underlying infrastructure are very diverse. The structural differences are an outcome of the circumstances of each region, existing infrastructure, and policy priorities of the relevant authorities. So far, ASEAN RPC is the only initiative with a sole focus on retail payments (Table 1). While this may change over time, many other retail payment initiatives have been built over an existing wholesale payment infrastructure or have been developed with such infrastructure. This unique feature of the RPC emerges from the strong linkages between the economies on the level of consumers and small businesses. The retail payments requirements from tourists, migrant workers, and MSMEs are significant, and the payment linkages help address the pain points of cost and speed of transfers.

28. The RPC is not centrally managed and, so far, relies on efforts of individual countries to establish and manage the payment linkages. In contrast, other payment initiatives, such as the PAPSS (through a centrally managed common, digital market infrastructure), TIPS (operated and overseen by the Eurosystem)[10], BUNA (operated by Arab Regional Payments Clearing and Settlement Organization, a subsidiary of Arab Monetary Fund), and SIP (managed by an institutional manager), are centrally managed. A centrally managed system can help oversee, standardize and harmonize various aspects of the payment initiatives, such as registration of participating institutions, control of operations, reporting, risk management, messaging, and dispute resolution. In this regard, a centrally managed system could be important for an integrated payment system of the ASEAN region.

29. The underlying agreements between the participating countries play an important role in the integration of payment systems. The ASEAN RPC is based on a MoU which encourages the integration of payment systems. In contrast, many other initiatives are driven by stricter mandates. For example, the BUNA was created due to a decision by the Council of Governors of the Arab Central Banks and Monetary Authorities to establish a cross-border, multi-currency payment system. The PAPSS is a flagship initiative of African Continental Free Trade Area, which aims to create a single market for goods and services. The SIP was established and operated under a legal framework established by the treaty on payment and securities settlement in Central America and Dominical Republic. The presence of a clear and consistent legal framework and cross-country agreements expedite the development of the payment integrations. On the other hand, the absence of hard

[10] The Eurosystem consists of the European Central Bank (ECB) and the national central banks of the eurozone countries. The ECB acts as the central operator of TIPS and is responsible for the initial setup, daily operations and overall governance of TIPS.

commitments could still allow for the development of integration organically i.e., driven by use cases and demand.

V. Challenges for the RPC in Integrating Payment Systems

30. For the RPC and the larger ASEAN+3 region, the prevalence of bilateral linkages poses a challenge to future growth and scalability. As of April 2025, eight ASEAN member economies had established bilateral connections from the national FPS with at least one other member economies via QR-payment linkages and fast payment linkages, along with private-led linkages between economies in the larger ASEAN+3 region. However, the establishment of bilateral linkages between economies requires substantial resources to harmonize the infrastructure, operational arrangements, and regulatory policies. The significant effort in setting up the bilateral linkages can be an obstacle in scaling up the payment initiatives. To put the numbers in perspective, if links are set up between each pair of RPC members, there would be 45 bilateral links. As shown in Figure 3, over the past six years, only thirteen bilateral links have been established between these members with Thailand leading the way with six bilateral links while Brunei and the Philippines yet to have an operational payment link with any of the ASEAN members.

31. The domestic focus of the payment systems is the primary reason for the difficulties in establishing the linkages. Typically, the national payment systems, including the FPS, are initially set up with a primary focus on domestic usage. In this context, the systems are optimized to suit the existing organizational arrangements, technological infrastructure, and laws and regulations in that country. While authorities involved in the development of these payment systems are aware of global standards and strive to adhere to them, the design of the system is weaved into available technologies and existing legal frameworks. This makes the systems across countries heterogeneous, making them difficult to integrate.

32. Broadly, integration issues can be divided into technical, regulatory, and governance issues.

- Technical issues include issues related to differences in standards and formats used for APIs, data, and messaging. For example, different data standards and formats can lead to fragmentation and truncated data leading to increased processing time and costs (BIS 2022). Similarly, the unique identification of customers can be done using different tokens in different jurisdictions. Some of these tokens include phone numbers, national identity or registration numbers, virtual payment address (VPA), and others.

- Regulatory issues are a consequence of different laws and regulations across jurisdictions. Data sharing, privacy and storage regulations, divergent implementation of AML/CFT laws, and different settlement finalities are a few examples of these differences. Notably, the divergent implementation of AML/CFT laws is a critical difference as countries could have different levels of FATF-compliant systems, inconsistent risk assessments (e.g., different thresholds for transaction monitoring), and differences in risk scoring for real time transaction monitoring.

- Governance issues arise from agreements, rules and operational aspects. For instance, differences in the requirements for participating institutions may restrict the payment service providers to only those who satisfy the criteria for both jurisdictions. The systems may have differences in service level agreements (SLAs) such as the maximum time in which the transfer happens. Dispute resolution protocols and loss-sharing also form an important source of disparity.

33. The integration issues are resolved using a combination of technological solutions and streamlining of processes. The integration of payment systems requires harmonization of technologies, regulations, and governance standards. However, as noted earlier, most payment systems have been designed and optimized to cater to domestic use cases. The cross-border integrations are considered only after the system is operational domestically. Therefore, changing these standards for the purpose of integration could have significant implications for the domestic use of the payment system. Therefore, authorities have refrained from introducing large scale changes to their payment systems to facilitate integration. Based on inputs received from authorities, the integrations require the authorities to work closely and find solutions which are mutually agreeable while respecting the laws and regulations of each other's jurisdictions. These include the use of technological solutions, process streamlining, and agreements on standards for the integration.

- Technological solutions can be innovatively used to bridge data and compliance related issues. These solutions include data masking (to address privacy concerns), standardization of data and messaging formats, automating compliance checks, and real-time monitoring of suspicious transactions. In the PPPN linkage between Singapore and Thailand, new modules were developed to enable real-time name screening to ensure compliance with AML/CFT requirements in the fast cross-border payment system and address differences in system design (Baker McKenzie, MAS, and BoT 2022).

- Process streamlining makes sure that the regulatory standards on either jurisdiction are met while improving efficiency, reducing costs and increasing transparency. Streamlining the processes help enable straight-through processing i.e. automated processing of payments from initiation to completion without manual intervention (BIS 2020).

- Standards related to service delivery include agreements on processing and settlement timelines, error and exception handling, and dispute resolution. In this regard, the standards for the payment integrations need to be defined in consultation with the stakeholders. These may include adhering to international technical standards, establishing minimum data requirements, and agreeing on various service level descriptions such as aliases, data formats, payment limits, timeouts and rules for dispute resolution.

VI. Policy Discussion and the Way Forward

34. As discussed in the previous section, integrating cross-border payment systems poses significant regulatory challenges. The cross-border payments transcend a wide range of laws and regulations. These include, but are not limited to, data and privacy protection, AML/CFT, KYC, licensing and authorization of payment service providers, consumer protection, currency conversion and capital flow management, cross-border taxation policies, settlement finality and cybersecurity. Different countries may have different sets of laws and regulations, or in some cases, there could be an absence of laws and regulations. The differences in organizational structures of regulatory bodies in each country can add to the complexity of integration.

35. While many jurisdictions share common regulatory frameworks – variations in implementation create practical barriers to harmonization. The FSB has identified regulatory misalignment as a key impediment to seamless payment integration, as it increases costs, delays transactions, and limits interoperability between national payment infrastructures (FSB 2024). For instance, data protection and privacy laws across countries can vary, and may have different practices for data sharing and storage. As cross-border transactions involve data from a minimum of two different countries and hence need a common ground for implementing these laws to cross-border transactions. Similarly, the extent of customer due diligence for KYC/AML requirements can be different across jurisdictions and the inconsistencies may cause delays or rejection in the payments.

36. Achieving harmonization is an inherently a gradual process, but can be accelerated through advancements in technology and cooperation. Though the primary focus of payment systems is to cater to the needs of the domestic economy, the authorities must adhere to international standards to the extent possible while designing the payments systems. As demonstrated by ASEAN members, diverse payment systems can be integrated using technological solutions and deeper cooperation between participating countries. However, the integration has been time and resource intensive. Therefore, it is important to adhere to international standards while designing new payments systems. Existing payment systems can be gradually aligned to these norms to ease future integration, while minimizing disruptions to the existing users.

37. Economies may also choose to implement a common international standard or engage bilaterally to facilitate integration. International best practices can be implemented for issues such as KYC/AML, to make sure that the practices are standardized. The recommendations provided by FATF provides global standards for AML/CFT, especially the requirement of including complete originator and beneficiary information, which helps detect the transfers by criminals and terrorists. The FATF also recommends sharing financial intelligence and taking collaborative actions to trace and curb money laundering and terrorist financing. APEC's Financial Regulators Training Initiative is one such program which aims to align KYC/AML in the region. The payment integrations may also consider BIS/CPMI best practices for SLAs to standardize service delivery. The APEC Framework also lists various considerations and risk management objectives for cross-border payments and remittances (APEC 2022). On the technological front, the differences in system design across systems can make any API adaptation difficult and suboptimal for broader expansion, requiring the need for API standardization. The adoption and implementation of ISO 20022 standards will ease the integration and scalability of the RPC. However, issues such as tax compliance may require much deeper cooperation between relevant authorities and the solution may include tax treaties and common reporting standards.

38. Multilateral collaboration can offer an effective solution to regional cross-border payment. The high costs of establishing bilateral connections not only hinder the scalability of regional payment connectivity but also pose challenges for smaller economies as low transactions volume results in lower incentives. Therefore, majority of payment initiatives worldwide focus on a centralized approach, either with a common platform model or with a hub-and-spoke model. In these models, economies can connect to the rest by establishing one single connection to or integration with the central system. These initiatives also encourage the standardization of payment standard at each economy and promote best practices.

39. A centralized hub-and-spoke model can offer a scalability solution for the RPC and could be the way forward. Initiatives such as Project Nexus by BISIH explore direct linkages between domestic FPS networks, allowing real-time transactions across borders without significant infrastructure overhauls. Instead of establishing multiple bilateral linkages between economies, an economy can instead connect to the Nexus system to gain access to all members. This is achieved by setting common API standards, ensuring compliance with ISO20022 messaging standards, setting up gateways to convert domestic payment formats to a common structure, setting up a rulebook which defines roles, responsibilities and operational rules for the participants, and establishing a governing body to oversee compliance, onboarding, and standardization. The governing body was set up in November 2024 by the BSP, BNM, BoT, MAS, and RBI and is known as the Nexus Global Payments (Nexus Global Payments).

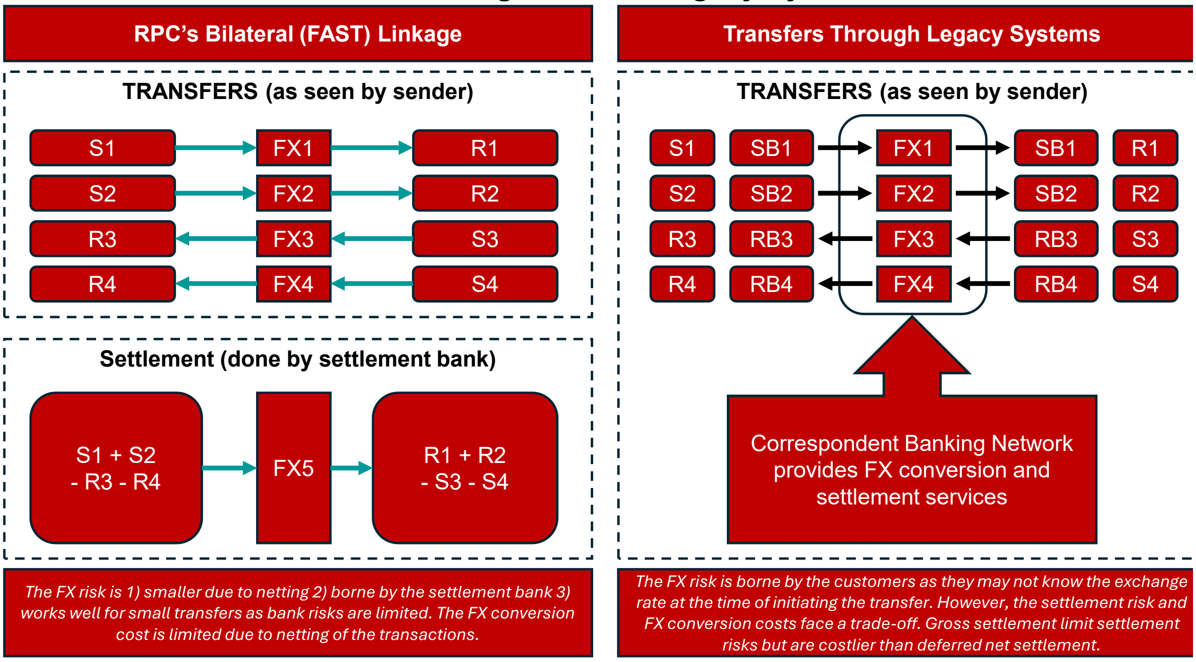
40. Beyond the core technological innovations, emerging technologies are being considered for the development and enhancement of regional payment initiatives. For instance, distributed ledger technology (DLT) is being explored for their potential to improve transparency, security, and efficiency in cross-border transactions, with some central banks looking into the potential role of Central Bank Digital Currencies (CBDCs) in cross-border interoperability. While not yet materialized in regional payment systems, cross-border CBDC initiatives such as Project Dunbar or mBridge showcase the technology's potential for instant, low-cost international transfers (Box 3). Another initiative, the Mandala project, between the BISIH, RBA, BoK, BNM, and MAS (2024), explored the possibility of streamlining cross-border payment compliance in a digital payment system. The project created a prototype that integrated compliance into machine-readable code to enable automation, resulting in faster compliance check. However, this innovation can only adapt quantifiable and configurable measures and require a highly digitalized payment system. Private institutions also used the DLT technology to develop private stablecoins or private DLT-based infrastructure to facilitate cross-border transactions, although the usage is limited to certain customers (Partior 2021, Gosh 2023, and SCB 2024).

41. As technology evolves and regulations are standardized, the scope of the ASEAN RPC can be enhanced further. The ASEAN RPC primarily focuses on cross-border retail payment solutions. This aligns well with the objective of the authorities to provide an efficient cross-border payment solution to individuals and businesses, including the MSMEs. However, as the regional integration deepens, the focus will likely broaden to integrate wholesale payment solutions, such as RTGS, in the region. This integration will help generate high value transactions and further reduce the costs associated with cross-border transactions. The integration of wholesale payment infrastructure can also provide a significant boost to local currency usage.

42. **However, the risks posed by cross-border payment integrations warrant a cautious approach towards integrating wholesale payments in ASEAN+3.** The larger transaction amounts involved in wholesale payments would need tighter risk management, stronger due diligence, compatible implementations of AML/CFT protocols and if applicable, effective capital flow monitoring and management measures. The expansion to wholesale payments will also need a higher level of consistency in fraud detection mechanisms and dispute resolution procedures. Cross-border connections facilitating large amounts of payments can also pose a risk from a capital flows perspective. The speed and ease of the transfers can make the capital flows more volatile and in extreme situations, may cause liquidity stress for institutions. These cross-border transfers depend on a chain of participants working seamlessly together, but the system is only as strong as its weakest link. Cybersecurity lapses, platform outages, data security breaches, and process failures at any participant could compromise the integrity of payment systems on either side of the linkage. While these risks also exist in retail payment integrations, the systemic risk is lower due to the regulated transaction sizes, and in many cases, the limited number of participating organizations.

43. **The extent of financial market integration will also be a key determinant of the RPC expanding to wholesale payments.** The existing payment linkages are bilateral and open for retail transactions with limits on the transaction size which limits the market risks faced by the participating banks. The participating banks accumulate and net-off the positions, before settling them at pre-determined times. Smaller transaction amounts and the netting of transactions make sure that the exchange rate risks carried by banks remain low (Figure 5). However, expansion to wholesale payments may facilitate the flow of large amounts through the linkage. This will require banks to have access to liquidity facilities or backstops in local currencies on either side, availability of hedging instruments and sufficient volumes to develop the relevant infrastructure for direct trading between local currencies on a larger scale (AMRO 2023). This calls for a significant development and integration of regional financial markets.

Figure 5. A Simplistic Representation of Settlement and FX Conversions in RPC's Bilateral Linkages versus Legacy Systems



Source: AMRO staff visualization.
Note: S = Sender, R = Receiver, SB = Sending bank, RB = Receiving bank, FX = Foreign exchange rate.

Box 3. Distributed Ledger Technology in Cross-Border Payment in the ASEAN+3

Distributed Ledger Technology (DLT) is a decentralized digital system that records transactions across multiple nodes (computers) in a secure, transparent, and tamper-resistant manner. Unlike centralized databases, where a single entity, such as a central server, controls data, DLT distributed the ledger among all participants in the network and synchronize the update with a pre-determined consensus process. This method allows the network to run without a centralized authority to manage while ensuring trust and security. Blockchain, the technology behinds cryptocurrencies such as Bitcoin, is a popular example of DLT.

For cross-border payments, DLT has the potential to reduce the needs for intermediaries, reducing delays and fees by allowing direct peer-to-peer settlements. DLT also supports multi-currency interoperability, making it easier to integrate central bank digital currencies (CBDCs) across borders. Additionally, DLT enables the use of smart contracts, which automate payments based on pre-set conditions, streamlining trade finance and remittances.

The ASEAN+3 economies have explored the use of DLT enhance regional cross-border payments. These economies have participated in exploration initiatives to experiment with and evaluate the use of DLT to create multiple-CBDC platforms to facilitate cross-border payments, such as project mBridge and Dunbar:

- Project mBridge is a collaboration between the Hong Kong Monetary Authority, the Bank of Thailand, the Central Bank of the United Arab Emirates, and the Digital Currency Research Institute of the People's Bank of China. The project developed mBridge Ledger, a DLT-based platform designed to facilitate real-time cross-border payments and currency conversion. In 2022, mBridge conducted a pilot involving 164 payment and foreign exchange transactions, totaling over $22 million (BISIH and others 2022a). Since 2024, the project has entered the minimum viable product (MVP) phase.

- Project Dunbar was a multi-CBDC initiative led by the BISIH Singapore Centre in collaboration with the MAS, the Reserve Bank of Australia (RBA), BNM, and the South African Reserve Bank (SARB). The project aimed to develop a shared settlement platform enabling multiple central banks to issue, hold, and transact with CBDCs directly, reducing reliance on intermediaries. As proof of concept, Dunbar successfully demonstrated that a multi-CBDC shared ledger could improve cross-border payment efficiency while maintaining central bank autonomy (BISIH and others 2022b). The project also identified key policy, regulatory, and operational challenges that would need to be addressed before real-world implementation. Completed in 2022, Project Dunbar provided valuable insights but has not progressed to further development or deployment.

Central banks in the ASEAN+3 region have also participated in other DLT-powered projects to explore other use cases, such as tokenization and automated market making usages (Bank of France, MAS, and BISIH 2023). While these efforts remain limited to exploratory phases, they underscore the region's growing interest in leveraging DLT for financial innovation. Moving forward, further collaboration, regulatory harmonization, and technological advancements will be crucial in determining whether DLT can transition from proof-of-concept projects to fully operational systems in cross-border payments and CBDC ecosystems.

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REDEFINING TRADE: HOW INDUSTRY 4.0 IMPACTS SERVICES FLOWS IN ASIA-PACIFIC

Ivan Cenon Bernardo[1]

Abstract

The growth of the ASEAN+6 tradeable service sector has consistently exceeded the rate of expansion of world services trade, highlighting the importance of the sector as a source of growth. This study explores the unique interplay and relationship between services trade and technology, specifically on the impact of the Fourth Industrial Revolution (IR 4.0) technologies on the trade patterns in the ASEAN+6 region. Applying the gravity model of international trade, the paper utilizes non-linear specifications to measure the impact of IR 4.0 technology in services trade. Results reveal that the home market effect holds, and the role of distance has diminished, hinting at the effect of digital trade. IR 4.0 has affected structural transformation to strengthen an economy's industrial base. FTAs mitigate uncertainties of services tradability with a partner economy, and the service sector is resilient against global shocks.

JEL: C23, C29, F13, F14, F15, F23, F63, O33

Keywords: Gravity Equation, Industry 4.0, Trade in Services

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Executive Summary

The world has ushered in a new age of structural transformation, rethinking the role of the service sector in the development of the national economy and cross-border exchange. Services trade has accounted for one-fifth of global output that has been maintained amidst the macroeconomic headwinds in recent decades.

The ASEAN+6 region is the epicentre of global demand and economic growth, accounting for 22.35% of global services trade. The development of the ASEAN+6 tradeable service sector has consistently exceeded the rate of expansion of the world service sector, proving that the sector is an important source of growth. However, this trend was interrupted by the adverse effects of the COVID-19 pandemic. The shift towards the development of a tradable service sector comes at a time when the region is reconfiguring its trade strategy to maintain its growth performance amidst the geo-political tensions, trade decoupling, and rise of automation.

This study explores the unique interplay and relationship between services trade and technology, specifically on the impact of the Fourth Industrial Revolution (IR 4.0) technologies on the trade patterns in the ASEAN+6 region.

A key impetus of the increasing importance of the tradeable service sector is the critical developments in the information and communication technology (ICT) sector. These developments are integral to the global value chains (GVCs) as they enable new business models and outsourcing opportunities in areas such as research and development (R&D), skills enhancement, and design (Miroudot & Shepherd, 2016).

This study applies gravity equation which is a standard workhorse models in international trade, particularly known for providing a better prediction than goods trade (Kimura & Lee, 2006). It was proposed that the optimum trade flows are determined by the exogenous size of the two (2) economies and their geographic distance. A significant advancement in the literature on gravity models is the examination of non-linear models. Researchers argue that, due to the inherent nature of the gravity equation, it should be estimated using its multiplicative form with a pseudo-maximum likelihood (PML) technique (McCullagh & Nelder, 1989; Santos Silva & Tenreyro, 2006).

Given the main research question, various proxy variables for IR 4.0 were used in the specification, including the share of modern services and goods exports and intellectual property. The gravity model was estimated using the Poison-PML (PPML) and Negative Binomial-PML (NBPML) estimation techniques. The regression results highlight the following:

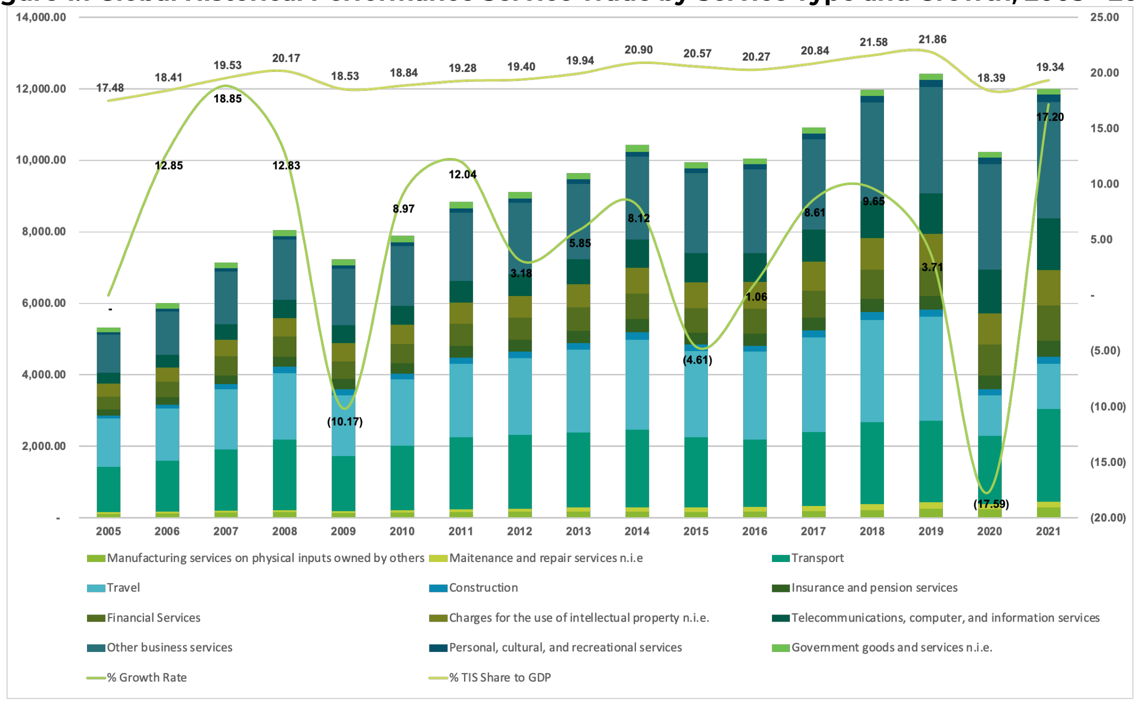
- the home market effect holds;
- the importance of distance to trade has diminished, likely due to digitalization;
- structural transformation supports a stronger industrial base;
- exchange rates matter in trade in services;
- FTAs mitigate risk due to uncertainties of its trading partners; and
- the tradeable service sector is resilient against global shocks.

I. Introduction

Global economic progress in the recent decade has shown substantial contribution from the developments in international exchange, especially from free movement of goods, financial markets, and people (Blanchard, 2021). As far as these developments are concerned, economists and industrialists have recognized the emerging role of services trade in the industrial development of an economy. This is accompanied by the disruptive nature of rapid technological advancement and innovation in the normal delivery of services[2] in the age of the Fourth Industrial Revolution (IR 4.0)[3]. These transformative technologies and key globalization trends have enabled an unprecedented expansion of the global services trade.

The world has ushered in a new age of structural transformation, rethinking the role of the service sector in the development of the national economy and cross-border exchange. Services trade has accounted for one-fifth of global output that has been maintained amidst the macroeconomic headwinds in recent decades (Figure 1.1). The contribution of services trade has grown from 17.48% in 2005 to 19.34% in 2021, withstanding the crippling impact of the Global Financial Crisis (GFC) in 2009, the productivity slowdown of 2015, and the COVID-19 pandemic in 2020.

Figure 1.1 Global Historical Performance Service Trade by Service Type and Growth, 2005 - 2021



Source: Author's Calculation; Liberatore & Steen (2021); World Bank (n.d.)

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[2] This paper follows the services discussed in the IMF's Balance of Payments and International Investment Position Manual, 6th Edition. Burgi-Schmelz, A., & Ducharme, L. M. (2014). Chapter 12. Services. In *BPM6 Compilation Guide: Companion document to the sixth edition of the Balance of Payments and International Investment Position Manual* (pp. 187–218). International Monetary Fund. https://www.imf.org/external/pubs/ft/bop/2014/pdf/guide.pdf

[3] This paper uses the term Fourth Industrial Revolution to indicate the encompassing role of Industry 4.0, Digital Economy, Digital Trade, Globotics, Second Machine Age, and the Rise of Robots as found in the recent literature.

The dynamics in the data are not new. As early as the 2000s, the expansion of international service transactions has been driven by continuous technological changes, liberalizing policy developments, and regional trade integration (Hardin and Holmes, 1997). Technological developments[4] and the internationalization of services are inseparable as technology allowed product differentiation and specialization, expanding services trade and its accessibility since the 1980s.

The ASEAN+6 region is identified as an important trading area in the world as it accounts for 22.35% of global services trade, most of which is highly concentrated in five (5) economies.[5] The performance of the service sector in the region in recent years has shown the unique interplay between the service and industrial sectors to spur economic growth. Such interplay led to the emergence of key economies in services in the region, such as Singapore, India, and the Philippines (Wiegand et al., 2024). The shift towards the development of a tradable service sector comes at the time the region is reconfiguring its trade strategy to maintain its growth performance amidst the geo-political tensions, trade decoupling, and rise of automation.

New technologies have allowed the delivery of modern services at a distance in contrast to traditional services that necessitate physical proximity. Additionally, service tradability has allowed economies to remain competitive and innovative to diversify and transition to a more sophisticated export basket, making it a key enabler for economies, especially emerging and developing economies.

This study will explore the unique interplay and relationship between services trade and technology, specifically on the impact of IR 4.0 technologies on the trade patterns in the ASEAN+6 region. The paper contributes to the emerging trade literature that discusses the factors and direction of services flow, accounting for the transformation undertaken by the economy in light of the IR 4.0. Results highlight the role of policy in the ASEAN+6 economies to sustain and expand the tradeable service sector.

The rest of the paper proceeds as follows: Section 2 presents stylized facts. Section 3 discusses theoretical and empirical work related to services trade and technology. Section 4 explains the estimation strategy. Section 5 presents the results. Section 6 concludes.

II. Stylized Facts

Development patterns have shown that an economy shifting towards the service sector faces the challenges in achieving high economic growth compared to an economy relying on its industrial base. In the Asia-Pacific region, certain economies faced a plateauing of total factor productivity (TFP) combined with a structural transition, given the deep integration into global value chains (GVCs) and demand reliance on advanced economies (Duval et al., 2014).

[4] The developments accounted for in this discussion are attributed to the Third and Fourth Industrial Revolutions, as mentioned in Schwab (2016).
[5] Based on available data, it has been observed that 4.51% of global trade is attributed to China, Singapore, India, Japan, and Korea.

From a development perspective, focusing on a service-based export economy has been attractive for middle-income and emerging economies since it only relies on the accessibility to electricity and the Internet, compared to the traditional high investment requirement needed to pursue the manufacturing sector (Baldwin, 2024).

It is worth noting that the ASEAN+6 region,[6] has been the epicentre of global demand and economic growth. This growth has always been dependent on external demand, compared to any other economic bloc or region. This led to the region being referred to as Factory Asia,[7] cementing its place as a key manufacturing hub for the world. The region continues to expect expansion and proliferation of its production network, making it a key advantage for a rebalancing strategy towards pushing more gains in the tradeable service sector and ushering progress in least-developed economies (Cardarelli, et al., 2010; Baldwin & Lopez-Gonzalez, 2015; Subramaniam & Ng, 2014).

Table 2.1 provides a comparative analysis of key indicators of the services trade for the ASEAN+6 and the world. The ASEAN+6 economies have expanded their contribution to the global tradeable service sector, with the average share increasing from 4.58% in 2011–2015 to 5.44% in 2016–2020. The growth of the ASEAN+6 tradeable service sector has consistently increased more than the rate of expansion of the world, proving that the sector is an important source of growth. However, this trend was interrupted by the adverse effects of the COVID-19 pandemic, especially in the transport and travel sectors. Within the region, it has been observed that almost two-thirds of services trade is equally attributable to travel, transport, and other business services.

Table 2.1. Comparative Table of Key Average Services Trade Indicators for ASEAN+6 and the World, 2011 - 2023

	Services Sector Growth Rate(%)		Share to Total Trade (%)[8]	
	World	ASEAN + 6	World	ASEAN + 6
2011 – 2015	4.92	7.00	20.88	4.58
2016 – 2020	1.01	1.32	23.49	5.44
2011 – 2020	2.96	4.16	22.18	5.01
2021 – 2023	14.16	13.76	22.35	5.14

Source: Author's Calculation; UNCTAD (2024)

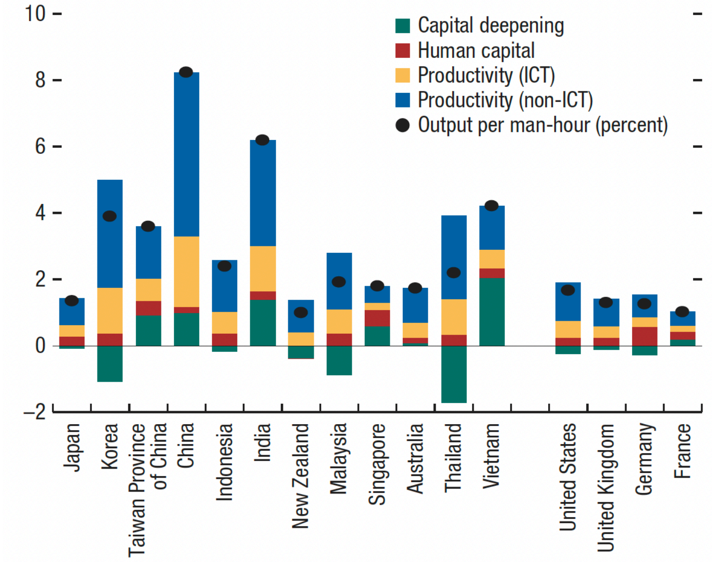
The Asia-Pacific region can leverage the existing innovation and research and development (R&D) environment to spur technological advancement and progress. The region's position complements its existing human capital to improve its short and long-term prospects, accounting for ~28.00% of per capita growth for the past two (2) decades (See Figure 2.1) (Mathai et al., 2018).

[6]The ASEAN+6 comprises the following economies: Australia, Brunei, Cambodia, China, India, Indonesia, Japan, Lao, Malaysia, Myanmar, New Zealand, Philippines, Singapore, South Korea, Thailand, and Viet Nam.

[7] Factory Asia refers to the model of regional production networks connecting factories in different Asian economies, producing parts and components that are then assembled, with the final product shipped mainly to advanced economies (Ando and Kimura, 2005).

[8] We account for both Goods and Services Trade.

Figure 2.1 Sources of Economic Growth in Selected Economies, percentage points; 1995 – 2016



Source: Mathai, Rhee, & Kang (2018)

The shift towards modern technology has been instrumental in identifying services trade as a more desirable form of commerce than goods trade, with the cost-saving strategy in place that has reshaped the way we think about globalization (Loungani, et al, 2017). Frontier technologies (e.g., Artificial Intelligence (AI), robotics, computing power, cryptography, big data, additive manufacturing, Internet of Things (IoT), E-Commerce, FinTech) can create positive productivity shocks that can alter the allocation of key resources and boost productivity and growth (Cazzaniga, 2024).

It is widely recognized that advanced economies in the Asia-Pacific (e.g., Singapore, Republic of Korea, Malaysia) can already concentrate on highly complex cognitive tasks, making them knowledge-intensive economies. This allows them to increase their TFP, keep their current competitiveness level, and generate new demand (Duval et al., 2014). However, this is not the case for emerging and developing economies in the region (e.g., The Philippines, Lao PDR), wherein the promise of technology-induced reductions is not yet realized, given the significant challenges faced by these economies (e.g., infrastructure gaps, institutional constraints, lower state of digitalization) (Chakravorti et al., 2020).

III. The Theory on Services Trade and Technology

<u>The Development and Concept of Tradeable Services</u>

A service can be thought of as an experienced good. Experienced goods are defined as goods that final consumers have imperfect knowledge of the product, indicating that there is information differentiation on the perceived quality and fit for preferences (Tirole, 1988). The definition fits the relative characteristics of a service given the highly differentiated offerings of a service provider. The assumption is that consumers only know one or few brands because the cost of experimenting with products is costly; thereby, not being able to validate the consumers' utility level.

Alternatively, to properly recognize the applicability of existing trade theories to services, it is necessary to explore the characteristics of a service and identify its similarities to a good.

In his seminal work, Hill (1977) summarized the definition of a service as the change in the condition of a person or of a good belonging to some economic unit, arising from the activity of some other economic unit, with the prior agreement of the former person or economic unit. In essence, a tradeable service has four (4) important characteristics. First, the intangibility condition, which focuses on the non-material nature of services that cannot be monitored, measured, and even taxed in the traditional metrics and scale as intended for goods trade. Second, the simultaneity condition, which emphasizes the innate interaction to produce and consume for the intended economic unit. Third, differentiation, which focuses on tailor-fitting to the needs of the final consumer. Lastly, joint production, which requires the participation of the final consumer or customer in the production process (Grünfeld & Moxnes, 2003; Hoekman & Mattoo, 2008).

Currently, there are two (2) predominant classification systems that provide an idea of the flow of services across international transactions. Following the General Agreement on Trade in Services (GATS), the Services Sectoral Classification is used to pursue and aid trade negotiations, given that the discussion of services trade was further emphasized during the conclusion of the Uruguay Round in 1994. Article 1 of the GATS proposes four (4) modes of supply for services, which are heavily influenced by the work of Sampson and Snape (1985).[9] Alternatively, the International Monetary Fund (IMF) introduced the Balance of Payments Manual, which summarizes the transactions between an economy and its trading partner. This includes the cross-border transaction that accounts services trade in the current account.

Technological progress has rapidly changed and revolutionized the tradeable service sector. Existing statistics and recompilation of services trade cannot capture the full contribution of the sector given the limitation imposed by the traditional service definition that understates the sector's value, particularly the indirect contribution to manufacturing (Guimarães-Filho, 2016). As such, efforts to enhance international statistics on services trade have been updated to reflect these developments. The current round of updates of the IMF Balance of Payments Manual 7th Edition (BPM7) has made some progress by disaggregating the high-level standard service categories into sub-categories to account for the changes in the service sector. For example, in its current proposal for BPM7, the *Telecommunications, computer, and information services,* and *Other business services* were split into sub-categories and introduced a new segment specific to *Research and development services,* and *Professional and management consulting services* (IMF, 2024).

A key impetus for highlighting the importance of the tradeable service sector is the critical developments in the new information and communication technology sector (ICT). The rapid development of ICT has impacted the importance and volume of services trade flow amidst deregulation and service

[9] The four (4) modes of supply of trade in services are Cross-Border, Consumption Abroad, Commercial Presence, and the Presence of Natural Persons (Sampson & Snape, 1985; Lee & Lloyd, 2002).

liberalization[10] at the multilateral and regional levels. Similarly, the service sector is also at the nexus of innovation, given the integral role of the sector and its output to the GVC through new business models and outsourcing opportunities in R&D, skills enhancement, and design (Miroudot & Shepherd, 2016).

Even though IR 4.0 technologies have already provided an avenue to strengthen further services flow, there are still impediments to services trade that have yet to be lifted, including license requirements, national content requirements, limitation of movement, repatriation of foreign profits, restriction in competitions and foreign direct investment (FDI), and the presence of state-owned enterprises (Grosso et al., 2015; Romao & Bernardo, 2023).

The Theory on Tradeable Service: A Gravity Approach

Most of the literature on international trade has focused on the theory and empirics of goods trade. It is only recently that the literature and analysis of services trade have gained attention, given its rapid growth in international transactions. However, there exists a debate in the literature on the applicability of the theories and methods to services trade.

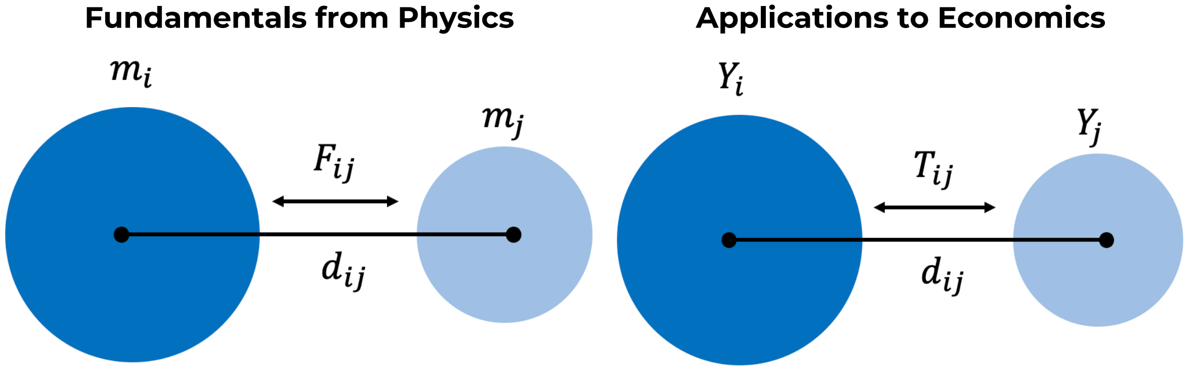
A survey of the literature shows a gap in the theoretical foundation on the behaviour of trade in services (TIS). The usage of the word 'good' in the initial writings of classical economists is only by tradition and not exclusion. As such, the ad hoc application of general trade theory is permitted (Hindley & Smith, 1984; Sampson & Snape, 1985; Lee & Lloyd, 2002).

To develop a comprehensive understanding to answer and predict the volume of trade, economics has borrowed Newton's fundamental law of gravity, which has now become a staple method of analysing international trade. The main analogy lies in the observation of planetary motions that posits planets are mutually attracted in proportion to their sizes and proximity, which mimics the trading behaviour of economies being proportional to their respective Gross Domestic Products (GDPs) and proximity (See Figure 3.1).

The gravity equation has been known as one of the standard workhorse models in international trade. It has also been applied to international migration, tourism, healthcare, agriculture and livestock, and investments (Anderson, 1979; Shahriar et. al., 2019). In international trade, it was initially applied in goods trade but is applicable to services trade, and it even provides a better prediction than goods trade based on the explanatory power of the adjusted R^2 (Kimura & Lee, 2006).

[10] Among the service liberalization mechanisms that need to be recognized include the General Agreements on Trade in Services (GATS), ASEAN Framework on Services (AFAS), Regional Comprehensive Economic Partnership (RCEP), and the Indo-Pacific Economic Framework (IPEF).

Figure 3.1 The Gravity Equation in Physics and Economics



$$F_{ij} = G\frac{m_i m_j}{d_{ij}^2} \qquad\qquad T_{ij} = a\frac{Y_i Y_j}{D_{ij}^2}$$

Wherein:

$\boldsymbol{m_i}$ = Mass of a particle or body i	$\boldsymbol{Y_i}$ = Economic mass for economy i
$\boldsymbol{m_j}$ = Mass of another particle or body j	$\boldsymbol{Y_j}$ = Economic mass for economy j
$\boldsymbol{d_{ij}}$ = Distance between the particle or body i with mass m_i and the particle or body j with mass m_j	$\boldsymbol{D_{ij}}$ = Geographical distance between economy i with economic mass Y_i and economy j with economic mass Y_j
$\boldsymbol{F_{ij}}$ = Force of attraction between the particle or body with mass m_i and the particle or body with mass m_j	$\boldsymbol{T_{ij}}$ = Force of trade flow between the economy with mass Y_i and the economy with mass Y_j
G = a constant, known as gravitational constant	a = a constant of variation

Source: Pal & Kar (2021)

The application of the gravity equation in international trade coincided with the development of the Heckscher-Ohlin (HO) model that responded to various criticisms and shortcomings of the dominant trade theories of the early 1950s. This includes Williams' (1929) classic criticism of mobility and immobility premises of trade theory and Weber's (1958) criticism of the significant impact of geographic distribution on industries reliant on the transportation sector that increases its transport cost of raw, intermediate, and final materials. While the HO model is explained using a portion of a general localization theory, emphasizing factor endowments, it fails to define the optimum volume of total trade and ignores spatial frictions.

As such, the initial concept of the gravity equation was based on exploring the interrelation of location theory and trade for short-run analysis of geographic flows and the structure of trade. It was proposed that the optimum trade flows are determined by the exogenous size of two (2) economies and their geographic segregation with both relationships expected to be present (Isard & Peck, 1954; Tinbergen, 1962; Bergstrand, 1985; Deardorff, 1998):

- The size of economy i (or the reporting economy), $\boldsymbol{Y_i}$, represents the general volume of demand or supply and the degree of product diversification. Hence, as an economy's diversification increases, it is expected to be less reliant on imports and vice versa.
- The size of economy j (or the partner economy), $\boldsymbol{Y_j}$, represents the capacity to provide or receive goods or services. Alternatively, this is the volume sold to an economy.
- As the distance from economy *i* to *j* tends to decrease relative to the rest of the world, ceteris paribus; effective demand and income potential between the two (2) economies increase.

The friction of distance plays a significant role in trade at all levels. Distance can be understood in two (2) ways: as opportunity costs or as an indicator of information about the destination market. Additionally, existing trade restrictions can account for any discrepancies between calculated and actual trade patterns.[11]

The foregoing is a significant departure from the dominant trade theories of the 1950s, which typically relied on a two-country, two-commodity framework (see Haberler, 1950) with zero or fixed transport costs assumption. Hence, Isard (1954) argues that the distance variable should be included to better account for spatial resistance and the complex, multilateral nature of trade among economies.

The basic model for the gravity approach is given as follows:

$$T_{ij} = \alpha_0 Y_i^{\alpha_1} Y_j^{\alpha_2} D_{ij}^{-\alpha_3} A_{ij}^{\alpha_4} U_{ijk} \qquad (1)$$

Where T_{ij} measures the total bilateral flows between reporting economy i and partner economy j. Y_i and Y_j represent the economic mass of economy i and j, respectively, while D_{ij} accounts for the geographic distance between economy i and economy j. A_{ij} are all other variables that may affect the total bilateral trade flow between the two (2) economies. The gravity model accounts for a log-normally distributed error term with $E\left(\ln U_{ijk}\right) = 0$.

The gravity approach has faced criticism for lacking a robust theoretical foundation despite demonstrating strong statistical explanatory and predictive power in empirical studies (Bergstrand, 1985). However, the literature has provided theoretical underpinnings for the gravity equation based on several key assumptions: constant elasticity function, homothetic preferences, differentiated products, imperfect specialization, impeded transaction cost, multilateral trade resistance, and Chamberlian monopolistic competition (see Appendix A for details).

IV. Data and Methodology

To estimate the gravity model, equation (1) is log-linearized:

$$T_{ij} = \alpha_0 + \alpha_1 Y_i + \alpha_2 Y_j - \alpha_3 D_{ij} + \alpha_4 A_{ij} + \gamma_{ij} + \delta_t + \varepsilon_{ijt} \qquad (2)$$

[11] Further explanations for this are detailed in Data and Methodology.

where δ_t denotes the time-fixed effects (FEs) and ε_{ijt} accounts for the random disturbance in the data. The economy-pair FEs, γ_{ij}, are included to account for multilateral resistance terms. In this specification, A_{ij} represents the various control variables, which include the variable of interest for the impact of IR 4.0 on services flow. A more detailed explanation is provided in the subsequent paragraphs.

Recalling the discussion on multilateral resistance, the exporter and importer FEs are also made to have a consistent estimate that can take advantage of its simplicity of implementation, reduce the assumptions needed for the model, and a proxy of remoteness. With inspiration from regional science, one can suggest that this is the force that "repulse" or "attract" trade flows for an exporter and importer, respectively (Feenstra, 2003; Arvis & Shepherd, 2013).

The standard ordinary least squares (OLS) method is noted to have problems in the presence of serious omitted variable bias, heteroskedasticity, and zero trade flow. The omitted emanates from the correlation of trade and GDP of an economy that is accounted for by the error term, ε_{ijt}.

A critical insight into the literature that has been highlighted is the presence of heteroskedasticity, even after controlling for the necessary FEs (Santos Silva & Tenreyro, 2006). This differential of the estimates may indicate the persistence of the Jensen inequality[12] in the estimation, meaning that the expected value of the logarithm of a random variable is different from the logarithm of the expected value, $E(\ln y) \neq \ln E(y)$, leading the output of the estimation to be misleading and meaningless. Given the dependence of the variance of the error term, ε_{ijt}, to the regressors, the expected value of $\ln \varepsilon_{ijt}$ will also depend on the regressors; thereby, violating the consistency requirement for OLS.

Similarly, zero trade flows make the results problematic and biased, specifically omitted and sample selection variables (Shahriar et. al., 2019). The presence of zeros is a natural trade phenomenon and transforming it into a log format will lead to an undefined value.

The case for zero trade will not imply the multiplicative form of the gravity model, but it will create a problem once the log-linearized format has been undertaken. This leads to inconsistent estimators of the key parameters, and the magnitude of the estimation will depend on the sample and model specification.

Deviating from the log-linearized method will ensure that the estimation model is robust against heteroskedasticity while still accounting for the multilateral resistance terms, as espoused by Anderson and van Wincoop (2003). Anchoring from the theoretical model of a constant-elasticity model, the pseudo-maximum family (PML) models are heavily used to achieve a more consistent estimate. The selection of the model will typically depend on the various factors of dispersion and the presence of excessive zeroes.

[12] Alternatively, one can look at Jensen's inequality when the total predicted trade exceeds actual trade (Arvis & Shepherd, 2013).

Poisson Pseudo-Maximum Likelihood (PPML) Model

A key advancement in the gravity model literature is the exploration of non-linear models, arguing that by the nature of the gravity equation, it should be estimated using its multiplicative form via a PML technique of the functional form $V[y_i|x]$(McCullagh & Nelder 1989; Santos Silva & Tenreyro, 2006).

The use of the Poisson distribution is warranted since it puts more focus on the consistency of the estimator, leading to less biased results from heteroskedasticity. It is also the only valid estimator under very mild assumptions and with models of high-dimensional FEs unaffected by non-existent estimates (Martin & Pham, 2020; Santos Silva & Tenreyro, 2022). Additionally, the method uses the hypothesis that the conditional variance is proportional to the conditional mean, meaning there is equidispersion in the model. As such, the PPML estimator has gained the necessary characteristics to estimate a constant-elasticity model consistent with the assumption of the gravity approach.

As a control for the multilateral resistance factor, the PPML estimate may be faced with an incidental parameter problem given the number of parameters generated by the reporting and partner dummies to control for the corresponding FEs (Santos Silva & Tenreyro, 2022). This can be resolved through pair-FEs (Baier & Bergstrand, 2007), instrumental variable, or Jochmans' estimator (Jochmans, 2017). The Jochman's estimator provides a more convincing method since it will no longer suffer from the incidental parameter problem by partialling out the origin and destination FEs.

Nevertheless, using the PPML estimate will overcome Jensen's inequality since it preserves the total trade flow between the actual and estimated bilateral trade flow, compared to other methods (Arvis & Shepherd, 2013).

Negative Binomial Pseudo-Maximum Likelihood (NBPML) Model

There are instances that the equidispersion might not hold, given that the conditional variance is often higher than the conditional mean driven by the unobserved heterogeneity of using the Poisson distribution, indicating that there is an overdispersion in the observation (Burger, van Oort, & Linders, 2009).

To correct for such an overdispersion, the negative binomial regression model is used because it provides the same expected value as the Poisson distribution, but the variance is specified as a function of the conditional mean and a dispersion parameter. This incorporates the unobserved heterogeneity from the omitted variable concern. One can think that there is an added error term.

Data and Controls for a Model of Services Trade

Bilateral Trade

The dependent variable, total TIS, used in this paper is the final value provided by the second alteration of the OECD-WTO Balanced Trade in Service (BaTIS) Database following the BPM6 configuration. With the intended goal of developing an international benchmark dataset for TIS statistics, the BATIS uses a top-down approach that utilizes the traditional WTO-United Nations Conference on Trade and Development (UNCTAD) TIS data as a starting point.

The paper looks at the annual services trade performance of the ASEAN+6 region and its 141 trading partners from 2005 – 2020. This translates to 1,960 unique observations across the years. Due to data limitations, Brunei and Myanmar were not included in the estimation.

The explanatory variables are as follows:

Gross Domestic Product

As an economy increases its GDP, its demand for services trade likewise increases as the economy expands the share of its service sector (Kimura & Lee, 2006).

Numerous studies in the field, including those explicitly applied to services trade, have looked at the strong and significant impact of the GDP of the reporting economy compared to the GDP of the partner economy; thereby, proving the presence of home market effects and the highly heterogenous nature of services (Tinbergen, 1962; Feenstra et. al., 2003; Grünfeld & Moxnes, 2003; Kimura & Lee, 2006). This home market effect is proven by the interrelationship of demand and the presence of variety, wherein, in a monopolistic competitive market, total demand will be equivalent to the size of the market.

The GDP data was obtained through the World Bank's Open Data and the IMF's World Economic Outlook Database.[13]

Distance

The preceding section highlighted the important role of distance in the interaction of the producer and consumer of a tradeable service. Services flow is expected to be reduced with distance if, in addition to physical distance, it proxies as the full transaction cost, which includes communications costs and cultural barriers (Bergstrand, 1989; Grünfeld & Moxnes, 2003; Mirza & Nicoletti, 2004; Anderson et al., 2014).

However, it must be noted that this is not a necessary condition for all tradeable service, given the rising question of geographic proximity and technological developments (Grünfeld & Moxnes, 2003). Similarly, reducing transaction costs (e.g., technological improvements) will not lead to the predicted result closer to the frictionless gravity case. Still, trade with distant partners will expand while existing trade partners are close neighbours will diminish, given the loss of the initial advantage of relative distances (Deardorff, 1998).

The data utilized in this paper was the harmonic mean of the distance available in the CEPII Database (Conte et. al., 2023). This is a weighted distance that uses the following specifications:

[13] A total of eleven (11) economies that were excluded, given the lack/incomplete data. These economies are the Anguilla, Netherlands Antilles, Cuba, Curacao, Cayman Islands, Eritrea, Montserrat, Democratic People's Republic of Korea, Serbia and Montenegro, and Sint Maarten.

$$distw\_harmonic_{ij} = \left(\sum_{k \in i} \frac{pop_k}{pop_i} \sum_{l \in j} \frac{pop_l}{pop_j} d_{kl}^{-1} \right)^{-1}$$

where pop is a measure of population, and d_{kl} is the distance from city k to l. It is worth noting that population share was used to proxy for economic activity to construct a weighted economy-to-economy distance of spatial distribution.

Contiguity

This dummy variable will be 1 if country pairs share a land border and 0 otherwise (Kimura & Lee, 2006). Various literature points out diverging levels of the significant impact of this variable; however, it is expected that adjacent economies have more intense trade contacts (Tinbergen, 1962; Bergstrand, 1989; Santos Silva & Tenreyro, 2006).

The data was obtained from the CEPII Database, which utilizes the ARCGIS's World Countries Generalized dataset.

Remoteness

This represents the relative distance of the economy to its trading partner. From a firm's perspective, it accounts the fixed cost and heterogeneity on aggregate prices (Chaney, 2008). This is a necessary variable to account for the multilateral effect and reduce the misspecification bias in the results. It is mentioned that more than the remoteness variable might be to capture other important trade barriers, given the absence of the border barriers and their disconnection to theory (Anderson & van Wincoop, 2003). Hence, the mixed reaction of adding such a variable given the minimal explanatory power it provides to the coefficient estimates and the adjusted R^2.

The remoteness variable was generated following an adjusted specification of Kimura & Lee (2006), as follows:

$$Remoteness_{it} = \frac{1}{\sum {GDP_{it}}/{GDP_w}} \times \frac{1}{dist_{ij}}$$

Share of Modern Services Exports

The share of modern services exports relative to total exports reflects the growing importance of these services in GVCs, particularly in areas such as pre-manufacturing, post-sales, and after-sales support (Haven & van der Marel, 2018). This variable is essential for understanding developments associated with IR 4.0, making it a key variable of interest for this paper. The services revolution has been driven by three (3) key global forces: technology, transportability, and tradability. These factors significantly influence the services flow from a region to its partner economies (Ghani & Karas, 2009). By controlling for the share of modern services within total trade, the analysis considers the potential impact of modernizing the trade basket. This includes recognizing technological advancements and the inherent complexities related to productivity. It is important to note that some emerging and developing economies gain more advantages than others by specializing in specific areas classified as modern services. These areas include:

- Manufacturing services on physical inputs owned by others
- Maintenance and repair services not included elsewhere (n.i.e.)
- Insurance and pension services
- Financial services
- Telecommunications, computer, and information services
- Other business services

This specialization allows these economies to better integrate into global markets and enhance their competitive edge.

Share of Modern Goods Export

Like modern services, IR 4.0 is rooted in the transformative nature of the manufacturing sector, especially noting the growth factor it drives in an economy. Utilizing the insights provided by the Competitive Industrial Performance (CIP) Index of the United Nations Industrial Development Organization provides a fundamental understanding of the economy’s progress as it leverages its industrial competitiveness.

The CIP is an output-oriented composite index that efficiently measures an economy’s capacity to allocate resources to industrialize and improve its business ecosystem (Cheng et al., 2023). Focusing on the industrial competitiveness dimension of the index, it looks at the capacity of its industrial base, the impact of the economy on the global scale, and the level of structural transformation. Hence, the specific segment of the CIP, the share of the economy’s medium and high-tech exports to the overall goods export of an economy was estimated. By using this variable, the analysis captures the potential structural transformation effect arising from the industrial strategies implemented by an economy as it commits itself to innovation, industrial linkage, and economies of scale. This is also a variable of interest for this research.

Intellectual Property

Understanding the landscape of IR 4.0 requires a nuanced examination of how intellectual property (IP) influences international trade. The notion that more innovative economies are expected to be more integrated and active in global transactions may be expected; however, evidence indicates a contrary trend. Palangakaraya, Jensen, and Webster (2017) highlight the existence of both the patent-refusal effect and the foreign patent bias effect, which significantly impact a firm's decision to engage in global trade. A primary concern for firms is the potential erosion of their monopolistic advantages, as granted by patents if they lack adequate safeguards when entering foreign markets. This apprehension is compounded by fears of encountering infringement cases without protective measures. Notably, sectors characterized by technological complexity exhibit a pronounced deterrent effect regarding participation in international exchanges due to these IP-related concerns.

The data was collected from the World Intellectual Property Organization, which consolidates data for patent, trademark, industrial design, and utility models for the nationality of the filer of the IP.

Exchange Rate

Exchange rates significantly impact TIS, influencing both the pricing of services and the competitiveness of service providers in international markets. When a country's currency appreciates, its services become more expensive for foreign buyers. This can lead to a decrease in services exports, as international clients may seek cheaper alternatives from countries with weaker currencies. Conversely, if an economy's currency depreciates, its services become cheaper for foreign buyers, potentially increasing export volumes.

The paper utilizes the real effective exchange rate (REER) from the Bruegel database, which provides the REER for 178 trading partners (Darvas, 2021).

Foreign Direct Investment

This research examines the important role of FDIs in developing services trade. FDI contributes to building the economic structure of a country by accounting for both past and current investments (Ahmad, Kaliappan, & Ismail, 2017). It serves as a key vehicle for capital development, enabling various sectors and industries to enhance their employment opportunities and production capabilities.

The data for total FDI was sourced from the flow of inward investment reported by the UNCTAD.

Service FTAs

This dummy variable takes a value of 1 if the two (2) economies have an ongoing free trade agreement (FTA), whether at the bilateral, regional, or multilateral level, and 0 otherwise. A specification from the CEPII database was used only to account for FTAs that involve the service sector and TIS.

In principle, participation in FTAs is expected to lower transaction costs and facilitate services trade (Bergstrand, 1989; Santos Silva & Tenreyro, 2006). This stems from the idea of trade creation and trade diversion, wherein the former focuses on the benefits of lower trade costs between the two (2) economies. In contrast, the latter focuses on lower imports costs from a supplying economy.

World Uncertainty Index

Hoekman and Shepherd (2017) observed that the domestic business environment and regulatory policies can segment markets by increasing trade and transaction costs. As a result, various scholars have sought to analyze this particular variable.

Several researchers have explored the concept of economic barriers using the Economic Freedom of the World Index to examine the relationship between economic freedom and performance in international trade. Tinbergen (1962) noted that economic restrictions create a gap between actual trade and the "theoretical" trade that could occur without such barriers. These trade impediments compel economies to take corrective actions to maintain a balance conducive to their respective balance of payments. Similarly, Grünfeld and Moxnes (2003) estimated that corruption discourages the volume of services flowing into partner economies.

This paper utilizes the World Uncertainty Index (WUI) developed by Ahir, Bloom, and Furceri (2022). This index provides comparable cross-economy data by counting occurrences of the word "uncertainty" in various Economist Intelligence Unit (EIU) country reports. A key strength of this index is its focused approach to analysing uncertainty as an economic and political phenomenon. It employs a standardized and structured process to ensure that data can be compared across different time periods and economies. Furthermore, the paper also explores the behavior and patterns of uncertainty; hence, the usage of the squared variable.

Additional controls were added to account for the impact of the GFC and COVID-19 pandemic, which are expected to have a deteriorating effect on TIS.

Table 4.1 lists the variables used in this estimation, their description, and expected impact on services trade.

Table 4.1 Summary of Expected Signs of Independent Variables

Variable	Description	Direction	Related Studies
Dependent Variable			
Total Services Trade	**Total Trade Value** Total and Final Value of Trade in Services in USD Billions	N/A	N/A
Traditional Gravity Variables			
GDP of Reporting Economy	**GDP of the reporting economy** in USD Billions	Positive (+)	Tinbergen, 1962 Bergstrand, 1985 Feenstra, et al, 2001 Freund & Weinhold, 2002 Grünfeld & Moxnes, 2003 Kimura & Lee, 2006 Choi, 2010 Benz & Jaax, 2021
GDP of Partner Economy	**GDP of the partner economy** in USD Billions	Positive (+)	
Harmonic Distance	**Distance (km, Harmonic Mean)** Population-weighted distance between most populated cities	Negative (-)	Isard, 1954 Bergstrand, 1985 Grünfeld & Moxnes, 2003 Mirza & Nicoletti, 2004 Kimura & Lee, 2006 Benz & Jaax, 2021
Extended Gravity Variables			
Contiguity	**Contiguity** Dummy Variable wherein contig = 1 if economic pairs are neighbours	Positive (+)	Tinbergen, 1962 Bergstrand, 1985 Kimura & Lee, 2006 Benz & Jaax, 2021
Remoteness of Both Economies	**Total Remoteness** The relative distance of the two economies in time t	Positive (+)	Kimura & Lee, 2006 Chaney, 2008
Industrial/Innovation Policy Variables			
%Share of Modern Service Trade *Square %Share of Modern Service Trade*	**%Share of Modern Services Trade** Percentage share of Modern Service to Total Services	Positive (+)	Bernardo, 2024

%Share of Modern Good Trade *Square of %Share of Modern Good Trade*	**%Share of Modern Goods Trade** Percentage share of Modern Goods to Total Goods	Negative (-)	Bernardo, 2024
Intellectual Property Fillings	**IP Filling** The total number of IP filling based on Origin.	Negative (-)	Benz & Jaax, 2021
Inward FDI of the Previous Year	**FDI** Total Inward Investment	Positive (+)	Ahmad, Kaliappan, & Ismail, 2017 Tee, Tham, & Kam, 2020
Inward FDI		Positive (+)	
Monetary Policy Variables			
REER of Reporting Economy	**Annual REER** Calculated Real Effective Exchange Rate	Ambiguous	Bergstrand, 1985 Freund & Weinhold, 2002 Ahmad, Kaliappan, & Ismail, 2017
REER of Partner Economy		Ambiguous	
Trade Policy Variables			
Service FTAs	**Service FTAs** Dummy Variable wherein rta_serv = 1 if economic pairs have existing FTAs tackling TIS	Positive (+)	Bergstrand, 1985 Grünfeld & Moxnes, 2003 Mirza & Nicoletti, 2004 Kimura & Lee, 2006 Benz & Jaax, 2021
World Uncertainty Index of the Reporting Economy *Square of World Uncertainty Index of the Reporting Economy* *World Uncertainty Index of the Partner Economy* *Square of World Uncertainty Index of the Partner Economy*	**World Uncertainty Index** Smoothed version of the index, averaged per year	Negative (-)	Bernardo, 2024
Interaction Variables			
Service FTAs x World Uncertainty Index of the Reporting Economy	Interacted Service FTA and WUI	Ambiguous	Bernardo, 2024
Service FTAs x World Uncertainty Index of the Partner Economy		Ambiguous	

Source: Author's Compilation

V. Empirical Results and Discussion

The gravity model was estimated using the PPML, and NBPML estimation techniques, column (2) does not include year and economy-pair FE in the estimates, while columns (1) and (3) do. Year FE try to capture macroeconomic factors that are not explicitly accounted for in the model, while economy-pair FE considers the multilateral resistance terms. Hence, succeeding discussions will rely on specifications (1) and (3).

Table 5.1 Determinants of Trade in Services in ASEAN+6

	Poisson Pseudo Maximum Likelihood	**Negative Binomial Pseudo Maximum Likelihood**	
	(1)	(2)	(3)
Log of GDP of Reporting Economy	0.52*** (0.01)	0.59*** (0.02)	0.52*** (0.08)
Log of GDP of Partner Economy	0.32*** (0.01)	0.75*** (0.01)	0.32*** (0.05)
Lag of Harmonic Distance	7.02*** (0.40)	-5.43*** (0.17)	52.65** (21.38)
Contiguity	15.79*** (0.91)	-0.14*** (0.05)	13.99** (5.80)
%Share of Modern Service Trade	-0.02*** (0.00)	0.02*** (0.00)	-0.02*** (0.00)
Square of %Share of Modern Service Trade	0.00*** (0.00)	0.00 (0.00)	0.00*** (0.00)
%Share of Modern Good Trade	-3.18*** (0.11)	-3.35*** (0.33)	-3.17*** (0.81)
Square of %Share of Modern Good Trade	3.22*** (0.10)	5.50*** (0.33)	3.21*** (0.76)
Intellectual Property Fillings	0.04*** (0.00)	0.00 (0.02)	0.04 (0.03)
Log of REER of Reporting Economy	0.12*** (0.02)	0.14* (0.08)	0.11 (0.15)

Log of REER of Partner Economy	-0.11*** (0.01)	-0.46*** (0.06)	-0.11 (0.10)
Log of Inward FDI of the Previous Year	0.00*** (0.00)	-0.01** (0.00)	0.00 (0.00)
Log of Inward FDI	0.02*** (0.00)	0.06*** (0.01)	0.02*** (0.00)
Service FTAs	-0.02** (0.01)	0.35*** (0.05)	-0.01 (0.05)
World Uncertainty Index of the Reporting Economy	-0.47*** (0.10)	-0.40 (0.97)	-0.46 (0.74)
Square of World Uncertainty Index of the Reporting Economy	5.87*** (0.74)	11.12 (7.31)	5.83 (5.42)
World Uncertainty Index of the Partner Economy	0.16*** (0.04)	-2.78*** (0.43)	0.16 (0.32)
Square of World Uncertainty Index of the Partner Economy	-0.75*** (0.13)	9.10*** (1.40)	-0.75 (0.98)
Service FTAs x World Uncertainty Index of the Reporting Economy	0.03 (0.06)	1.41** (0.62)	0.02 (0.42)
Service FTAs x World Uncertainty Index of the Partner Economy	0.31*** (0.04)	-0.65 (0.40)	0.31 (0.27)
GFC Dummy	0.10*** (0.01)	0.10*** (0.03)	0.10* (0.05)
COVID Dummy	0.13*** (0.01)	-0.48*** (0.04)	0.13 (0.09)
Log of Remoteness of Both Economies	0.00*** (0.00)	0.00* (0.00)	0.00** (0.00)
Constant	-73.56	3.93	-125.70

	(3.75)	(0.65)	(47.80)
Year Fixed Effects	Yes	No	Yes
Economy-Pair Fixed Effects	Yes	No	Yes
Number of Observations	31,318	31,318	31,318
R-squared	0.99	0.81	0.94
Ramsey Regression Equation Specification Error Test (p-value)****			
Fitted Values Squared	0.11	0.12	0.87
Fitted Values Cubed	0.15	0.11	0.80

Source: Author's Compilation
*Note: *,**,*** indicates statistical significant at the 10%, 5%, and 1%, respectively. (#) are robust standard errors.*
*****Ho: The model has no omitted variables or incorrect functional form.*

The regression results highlight the following:

Finding 1: The home market effect holds

The coefficients for the reporting and partner economies' GDP of the same magnitude in specifications 1 and 3, at 0.52 and 0.32, respectively. These results are consistent with the traditional gravity model, which states that larger economies tend to trade more with each other. Additionally, the results suggests that there is indeed a presence of a home market effect - countries with significant domestic demand for services will also tend to produce and export those services. This is particularly true for products that benefit from economies of scale and incur high transportation costs.

Finding 2: The role of distance in services trade is muted

Regression results of the two (2) specifications show that the distance variable is positive with a coefficient of 7.02 and 52.65 for the PPML with FEs specification and NBPML with FEs specification, respectively. Although this contradicts the initially expected sign, this result is unsurprising. This validates the findings of Benz, Jaax, & Yotov (2022), who explored the decreasing role of the proximity burden, especially accounting for the development of transportation and ICT. Specifically for the ASEAN+6 economies, the results imply that geographical proximity is no longer a challenge, which is consistent with the emerging services trade activities located in the region, primarily IT-BPM and finance hubs.

However, the results also make a stark argument to the initial findings of Deardoff (1998), who mentioned the diminishing trade with close neighbours given the loss of initial advantage. This is signified by the positive and highly significant coefficient of the contiguity variable, implying that the digital economy can act as a trade creation mechanism to expand the menu of trading partners of an economy.

Finding 3: Structural Transformation Supports a Stronger Industrial Base

The results for the share of modern services trade and the share of modern goods trade suggests that, the direction of IR 4.0 and emerging technologies is reducing the trading intensity across economies. Results suggest that a percent increase in modern services trade leads to a 2% reduction in the total services trade, which is expected to plateau as the share of modern services trade increase.

The selection of an economy to prioritize a sector is also evident in the substantially large impact of the share of modern goods and its impact on services trade. It is expected that services trade will be reduced at an increasing pace for every percentage increase in the share of modern goods trade. This signifies that an economy capable of producing high and medium technological goods can pivot its resources from producing services to technological manufacturing. The additional productivity enhancements and cost-saving strategy captured by the manufacturing sector is not new. It was already documented in Asia that there is indeed an interaction between the developments of the manufacturing and service sector (Shepherd, 2019). This complicated dilemma has been drive policy considerations as economies must decide on the priority, at the expense of the other sector. This anchors back to the generalized trade balance relationship that indicates when a country has a surplus in goods, it must be accounting a deficit in its services account, and vice versa.

A reassuring evidence that can be observed is the role of FDI in the tradeable service sector. A significant and positive effect of FDI was obtained from both specifications, wherein a 2% increase in TIS is expected for every unit increase in contemporaneous investments. These investments illuminate opportunities for emerging and developing economies across the region and support their industrial journey toward leapfrogging to IR 4.0. Despite investing heavily in their service sectors, these economies can still catch up and strengthen their industrial bases. This is achievable by harnessing the knowledge and technological advancements that arise from the unique interactions facilitated by the tradeable service sector.

The region must adopt more adaptive strategies to effectively address the risks associated with digitalization. This approach is essential for fostering competition and innovation and reforming an economy's visions regarding trade and investment policies (Mathai et. al., 2018). Asia is well-positioned to capitalize on the advantages of a hyperconnected and digital trading system, as its per capita growth has accounted for one-third of digital innovation over the past two (2) decades. Therefore, economies must enhance their transformation strategies. This will enable them to effectively integrate technology—particularly e-commerce—into their operations, leading to higher labor productivity and facilitating the emergence of new market roles.

Finding 4: Exchange rate matters in TIS

The REER variable shows significance only in the PPML model with FE. It exhibits a strongly significant effect of 12% on services trade for every unit increase in the reporting economy's REER. In contrast, it demonstrates a highly significant and services trade-reducing effect of 11% for every unit increase in the partner economy's REER. As an additional measure, shifting from a REER variable to the explicit bilateral exchange rate indicates a positive and significant impact of the exchange rate in the NBPML model with FE (see Appendix B).[14]

The overall interpretation of these results is ambiguous because both currency appreciation and depreciation can have opposing impacts on trade dynamics. To ascertain the effect of the REER on TIS, a decomposition of imports and exports of services is necessary to understand the REER influence on trade outcomes. Standard trade theory predicts that a currency appreciation will reduce an economy's net exports as it makes exports less competitive and imports relatively cheaper.

Finding 5: FTAs mitigate risk due to uncertainties of its trading partners

The coefficient of the WUI suggests that uncertainty reduces trade for the reporting economy at an increasing rate (Nana, Ouedraogo, & Tapsoba, 2024). An opposite trend can be observed for the partner economy . The signs of the partner economy may indicate that although it continues to engage in activities and transactions with its partners to fulfil its economic requirements, the reporting economy monitors the situation if a crisis escalates.

However, the positive coefficient of the interaction term between the WUI of the partner economy and that FTA implies that FTAs play a crucial role in alleviating concerns for partner economy. They act as a buffer, helping to stabilize overall TIS for an economy, even in uncertain conditions.

Finding 6: The Tradeable Services Sector is Resilient

In contrast to the expected impact of the two (2) global phenomenon, it is shown that amidst the GFC and COVID-19 pandemic, services trade continues to increase by 10 – 13%. This implies that amidst global shocks in both the consumer and economic environment, services trade can provide the necessary buffer for economies to mitigate losses.

Transition to the service sector during the GFC is guided by a more pragmatic decision of stakeholders, particularly households, given the sector's resiliency against severe economic conditions. As such, the renewed call for structural reform has already started following the aftermath of the COVID-19 pandemic and the array of modern services currently in the market. This has triggered a clamour to move to high-technology and knowledge-intensive economies, which is consistent with the emerging evidence of the absorptive capacity of the service sector to ensure productivity growth, as the traditional delivery of services (e.g., teleworking) has been altered to accommodate the promises of IR 4.0.

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[14] As shown in Appendix B, the shift towards a bilateral exchange rate variable will lead to accepting the NBPML model with FE alone, given that the RESET indicates a specification error in the first 2 models.

VI. Conclusion

This paper identifies key findings regarding the impact of IR 4.0 on trade.

First, large trading partners continue to engage actively and increase trade intensity in the region, perhaps influenced by their positions within various GVCs and their roles in value-added trade.

Second, digital and structural transformations are challenging established trade theories. Specifically on the impact of distance, technological advancements have opened doors for unconventional trade partnerships, moving beyond traditional goods partners.

Third, shifting towards higher-value manufacturing and a more knowledge-intensive economy necessitates a reallocation strategy. This highlights the need for a focused and nuanced policy approach for the ASEAN+6 economies.

Lastly, the resiliency of the service sector is a buffer for an economy amidst uncertainty. Hence, economies are suggested to identify the policy measures, specifically on the industrial, trade, and monetary front, to enhance their service sector.

Future extensions of this research will explore emerging areas in services trade, particularly as data becomes available on the impacts of digital trade and servicification, and GVC intensity and participation.

It is also recommended to look into other models that can complement the gravity analysis, particularly the computable general equilibrium (CGE) and machine learning (ML) models. This will provide an additional perspective on the capability to explain trade flows, anchoring on their explanatory powers for various parameters and computational processes.

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Appendix A: Key Assumptions of the Gravity Equation

A. Constant-Elasticity Function

From an expenditure system approach anchoring in traded and non-traded goods, under an unrestricted approach, the Constant Elasticity of Substitution allows for the demand function to account for decisions between traded and untraded goods (μ_j) and among untraded goods (σ_j) (Bergstrand, 1985).

Similarly, on the production side, the Constant Elasticity of Transformation allows the production function to distinguish between home and foreign markets (η_i) and among export markets (γ_i).

As such, employing a constant elasticity function in the demand and supply equations allows differentiation in the two-stage decision process of consumption and production.

B. Homothetic Preferences

The individual demand for traded goods is determined in a homothetic utility function subject to a budget constraint. Imposing the separability condition and the identical homothetic function allows the expenditure share for any good to be identical across any economy. This indicates that economy i will purchase a traded good from economy j based on its share to expenditure, ${}^{Y_i}/_{Y_w}$, where Y_w is the world GDP.

C. Differentiated Products

In a multi-country and multi-product framework, it is well suited that there is a need to explain the bilateral trade flows in the presence of heterogenous products and origins, complemented by the increasing returns of scale of a firm; thereby, it is expected that intra-industry trade arises as the economy simultaneously imports and exports a variety of the products (Bergstrand, 1989; Evenett & Keller, 2002). Accounting for this factor, the national tariffs and transport costs still bias the estimation.

Using this approach, it is expected that the efficiency gains of using the gravity approach still dominate the bias created by any costs (e.g., transit cost, trade taxes) (Anderson, 1979). However, it is recognized that the revealed resistance, on average, provides an overview of the different treatments of each output produced by each economy in varying disaggregation (Anderson & van Wincoop, 2003).

As such, it is expected that the demand for the individual variety of output will become relatively insensitive in a highly differentiated product, as in the case that elasticity of substitution (σ_j) is low, hinting at minimal impact to the intensive margins of trade (Chaney, 2008).

D. Imperfect Specialization

It has been mentioned that perfect specialization models tend to overpredict the volume of trade compared to the actual realized amount, anchoring in the strict proportionality between GDP (or income) and trade. At the same time, there is rising evidence that consumers are not only purchasing a subset of the available varieties in the market. This creates evidence for an imperfect specialization case amidst the heterogenous product assumption (Evennett & Keller, 2002; Haveman & Hummels, 2004).

In the findings, global data supports the parameters imposed by a unicone HO model, indicating that homogenous goods are still produced in imperfectly specialized economies. The model will hold even in the large factor proportion difference. As a whole, the total volume of trade is dependent on an economy's summative share of income. This trade share measures the extent of specialization, especially since each economy is the sole supplier of an exported output.

The discussion is empirically consistent with the bilateral trade pattern. It must be emphasized that importer economies do not value the sources of outputs but consider sourcing an output at the least cost (Haveman & Hummels, 2004). This is consistent as trade cost is identified to be arbitrarily rising in terms of distance.

E. Impeded Transaction Cost

Without consideration of the factor price equilibrium, there are two (2) sets of outputs expected: those that are traded and those that are nontraded. These outputs can still compete in the same market if the transaction costs exactly equal the difference in production costs. As such, a consumer from economy i will decide to consume a good produced domestically or by a foreign supplier (Deardorff, 1998). The assumption of a highly differentiated product will exacerbate the consumer's decision since it will see a product from each economy as unique and distinguishable.

Hence, transaction costs take Samuelson's "iceberg" form, t_{ij}, wherein the portion of the transaction costs accounts for the loss of the output as it is transferred from economy i to j, $t_{ij} - 1$. It is expected that the relative distance of economy j from economy i is greater than the recorded average since this is always in unity, given the presence of transportation costs, the economy's purchases in the domestic market will be more than expected compared to the prediction of the simple frictionless gravity model.

F. Multilateral Trade Resistance

Geographic barriers affect bilateral trade volumes through the multilateral resistance variable. The seminal paper of Anderson & van Wincoop (2003) introduced the concept of multilateral trade resistance that accounts for the resistance to trade of an economy to other regions on average based on the border and distance of the economy. Although not entirely observable, the price index P_i is referred to as the multilateral resistance given its dependence on the total bilateral distances; hence, interpreting a rise in trade barriers with all trading partners will raise the index. This is not similar to the consumer price level. The multilateral resistance of P_i is homogenous, with a degree 1/2 in the trade cost.

It is cautionary to take note of the possible omitted variable bias that may occur in the interpretation of the distance and border. This factor has been identified to have three main components: the bilateral trade barrier between regions i and j, i's resistance to trade with all regions, and j's resistance to trade with all regions.

G. Chamberlian Monopolistic Competition

The development of the gravity equation also included the expansion to account for the Chamberlian monopolistic competition that dictates the capability of firms to hold monopoly power, but profits will be driven back to zero as the entry of firms participate in the market (Helpman 1987; Bergstrand, 1989; Feenstra et.al, 2002). A symmetric equilibrium with balanced trade implies that firms from large economies make positive profits or firms from small economies lose. The price of any output must be lower in the large market, and firms are located disproportionately, leading to higher exports from a large economy.

The market can determine total world output by keeping the heterogenous products and free factor mobility assumptions. This now creates an opportunity that relates the economy's size and the presence of monopolistic competition, signifying that as the size of the economy continues to increase, it will determine the relative volume of highly differentiated product trade. Hence, if the product is only produced by a single nation, the economy's relative size predetermines the trade flow in a highly specialized world.

As such, the extended model accounting for the above-stated assumptions follows the theoretical specification:[15]

$$M_{ij} = (\gamma_v^j - \gamma_v^i)\frac{m_i \phi_i Y_i \phi_j Y_j}{\sum_j \phi_j Y_j} \times \frac{1}{t_{ij}} \times \frac{\rho_{ij}^{1-\sigma}}{\sum_h \theta_h \rho_{ih}^{1-\sigma}}$$

where M_{ij} is the foreign port value, and m_i represents the trade imbalance due to long-term capital transactions represented as $m_i = m(Y_i, N_i)$. ϕ_i/ϕ_j is the share of expenditure on all traded goods in the total expenditure of economy i or j. γ_v^i is the share of good Z in the economy i's GDP in a specific industry/sector class. θ_i is the economy i's share of world income, and ρ_{ij} is the relative distance from suppliers.

[15] The specification of the model is derived based on the insights provided by Anderson (1979), Deardorff (1998), Evenett & Keller (2002), and Anderson & van Wincoop (2003).

Appendix B: Robustness Checks

Additional estimations were undertaken to ensure robustness of the results. A similar model and method were applied in the exercise, as shown in Table B.1, indicating the direction and intensity of the identified parameters.

Overall, the estimations indicate that the results are aligned with most cases already presented in the discussion. However, caution is required regarding the suggested parameters, given their failure to satisfy the RESET.. Only the NBPML model (3b) with FE pass the RESET, hence, succeeding discussion is based on this model's results.

To introduce temporal dynamics in the model the dependent lag variable was included. Across all estimations, it is observed that the impact of the lag variable is minute and often insignificant. This may indicate that the continuous engagement with trading partners in the service sector is not inhibited by previous performance, accounting for the highly competitive nature of services trade. This is consistent with our theoretical assumption, as indicated in Appendix A.

Next, a shift from a bilateral exchange rate measure was undertaken from the original REER specification for origin and destination economy. Results highlight a significant 8% increase for every unit increase in the bilateral exchange rate measure. This is consistent with the initial result, as shown in the PPML model with FE (model 1). More investigation and refinements may be needed to ascertain the impact of the exchange rate on services trade.

Table B.1 Additional Determinants of Trade in Services in ASEAN+6

	Poisson Pseudo Maximum Likelihood	**Negative Binomial Pseudo Maximum Likelihood**	
	(1b)	(2b)	(3b)
Log of GDP of Reporting Economy	0.59*** (0.01)	0.49*** (0.02)	0.59*** (0.04)
Log of GDP of Partner Economy	0.31*** (0.01)	0.75*** (0.01)	0.31*** (0.04)
Lag of Harmonic Distance	7.20*** (0.41)	-4.92*** (0.17)	53.38** (20.91)
Contiguity	16.51*** (0.92)	-0.18*** (0.05)	14.51** (5.67)
Lag of Services Trade	0.00 (0.00)	0.01*** (0.00)	0.00 (0.00)

%Share of Modern Service Trade	-0.02*** (0.00)	0.02*** (0.00)	-0.02*** (0.00)
Square of %Share of Modern Service Trade	0.00*** (0.00)	0.00 (0.00)	0.00*** (0.00)
%Share of Modern Good Trade	-1.74*** (0.10)	-3.21*** (0.30)	-1.74** (0.73)
Square of %Share of Modern Good Trade	1.79*** (0.10)	5.45*** (0.30)	1.79*** (0.68)
Intellectual Property Fillings	0.00 (0.00)	0.00*** (0.01)	0.00 (0.03)
Log of Bilateral Foreign Exchange	0.08*** (0.01)	0.00 (0.00)	0.08** (0.04)
Log of Inward FDI of the Previous Year	0.00*** (0.00)	0.03*** (0.00)	0.00 (0.00)
Log of Inward FDI	0.02*** (0.00)	0.06*** (0.01)	0.02*** (0.00)
Service FTAs	-0.04** (0.01)	0.37*** (0.04)	-0.04 (0.04)
World Uncertainty Index of the Reporting Economy	-0.23** (0.09)	0.05 (0.92)	-0.22 (0.67)
Square of World Uncertainty Index of the Reporting Economy	3,51*** (0.69)	7.08 (6.92)	3.46 (4.88)
World Uncertainty Index of the Partner Economy	0.16*** (0.04)	-1.69*** (0.40)	0.16 (0.29)
Square of World Uncertainty Index of the Partner Economy	-0.80*** (0.12)	7.48*** (1.25)	-0.81 (0.83)
Service FTAs x World Uncertainty Index of the Reporting Economy	0.24 (0.05)	1.04* (0.60)	0.23 (0.39)

Service FTAs x World Uncertainty Index of the Partner Economy	0.30*** (0.03)	-1.15*** (0.35)	0.30 (0.23)
GFC Dummy	0.08*** (0.01)	0.12*** (0.03)	0.08* (0.04)
COVID Dummy	0.11*** (0.01)	-0.51*** (0.04)	0.11 (0.07)
Log of Remoteness of Both Economies	0.00*** (0.00)	0.00*** (0.00)	0.00** (0.00)
Constant	-75.73 (3.79)	0.89 (0.38)	-127.87 (46.80)
Year Fixed Effects	Yes	No	Yes
Economy-Pair Fixed Effects	Yes	No	Yes
Number of Observations	34,500	34,500	34,500
R-squared	0.99	0.84	0.95
Ramsey Regression Equation Specification Error Test (p-value)****			
Fitted Values Squared	0.00	0.00	0.66
Fitted Values Cubed	0.00	0.23	0.37

Source: Author's Compilation
*Note: *,**,*** indicates statistical significant at the 10%, 5%, and 1%, respectively. (#) are robust standard errors.*
*****put the same footnote as in Table 5.1 here*

Artificial Intelligence and Intangible Capital in the ASEAN+3 Region

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Preliminary and Incomplete. Please do not circulate.

Abstract

This paper explores the evolution and characteristics of intangible capital among firms in four ASEAN+3 economies with deeper financial markets, benchmarked against the United States. Our findings reveal significant variations in the accumulation paths of intangible capital across these economies, underscoring the pivotal role of knowledge capital in accelerating intangible capital accumulation in the last decade. Employing an interrupted time series design, we present empirical evidence that the advent of widely accessible deep learning in 2016 and generative artificial intelligence in 2021 represent critical milestones that have influenced intangible capital investment in several of the economies under study.

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1. Introduction

Intangible capital, encompassing knowledge capital, such as research and development (R&D) investments, software development; and organizational capital, including human resources, management practices, has increasingly been recognized as a pivotal asset for economic growth and firm competitiveness. Despite its universal significance, standard accounting treatment makes it difficult for firms to recognize intangibles as assets.

This discrepancy is evident in the high price-to-book ratios of the five firms with the largest market capitalizations globally, ranging from 67.8 times (Apple) to 7.47 times (Google) as of 2024, suggesting that physical capital can only account of a small proportion of these giant firms' values. While there is a growing academic literature on firm-level intangible capital, it predominantly focuses on the United States (Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017) and Europe (Bontempi and Mairesse, 2015; Marrocu, et al., 2012). This leave a notable void in understanding the dynamics in other regions.

This study seeks to fill the gap by examining the characteristics and evolution of intangible capital of both public and private firms in Hong Kong, Singapore, South Korea, and Japan. The selection of these four economies, which have more developed equity markets in the region, was guided by cross-economy evidence suggesting that the development of an economy's equity market is positively correlated with the size of its high-tech sector and the intensity of innovation (Hsu et al., 2014; Brown et al., 2017).[1] As these economies transitioned from manufacturing- and service-based to knowledge-intensive structures, the role of intangible capital becomes increasingly critical in driving innovation and economic development (Bloom et al., 2012; Bresnahan, et al., 2002; Brynjolfsson et al., 2002). This shift underscores the need for a comprehensive analysis of the role of intangible capital in these markets and understanding its boarder economic implications.

[1] In 2022, the market capitalization of listed domestic companies as a percentage of GDP ranked Hong Kong 1st, Japan 11th, Singapore 12th, and South Korea 17th globally, according to the World Bank (https://data.worldbank.org/indicator/CM.MKT.LCAP.GD.ZS?most_recent_value_desc=true)

Using a comprehensive dataset of firm-level financial statements from Standard and Poor's (S&P) Capital IQ Pro (CIQ) database, this paper examines the accumulation of intangible capital in the four selected ASEAN+3 economies and the United States (US). Our analysis spans the period from 2012 to 2023, with a focus on the impact of technological advancements, particularly the widespread adoption of deep learning in 2016 and the emergence of Generative Artificial Intelligence (GenAI) in 2021.

Marked as one of the most important milestones in AI development since 2010, deep learning is a subset of machine learning that employs algorithms inspired by the brain's structure and function. This technology enables computers to learn from vast amounts of data, enhancing their pattern recognition and decision-making capabilities without human intervention. GenAI, which utilizes deep learning techniques, generates new and realistic content, such as text, images, or music, based on its training data. As the realization of AI's potential heavily relies on knowledge and organizational capital rather than physical assets, we hypothesize that the advent of deep learning and GenAI may stimulate the accumulation of intangible capital.

We apply a perpetual inventory method, which is standard in the literature, to consistently estimate the stocks of knowledge capital and organizational capital, which are then combined to form total intangible capital at the firm-level (Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017; Van Criekingen et al. 2022). Our estimates show significant variations in the accumulation paths of intangible capital across economies, with the US, Hong Kong, and Singapore exhibiting an acceleration of intangible capital formation since the GenAI breakthrough in 2021, primarily driven by the knowledge capital. In contrast, Japan and South Korea display a decline and stability in intangible capital accumulation, respectively, since the early 2010s.

We then utilize an interrupted time series (ITS) design to estimate the impact of deep learning developments since 2016 and GenAI advancements sicne 2021, on the accumulation of intangible capital in the five economies. This method is particularly suited to our analysis as it allows for the assessment of changes in investment trends following specific milestones, without the need for an observable control group, which is unfeasible in this context due to the universal exposure of firms to technology (Bernal et al., 2017, 2021).

Our results suggest that the introduction of GenAI is associated with an acceleration of intangible capital accumulation in the four ASEAN+3 economies and the US. In contrast, the estimated effects of deep learning were smaller in the near term across economies, highlighting the importance of economy-specific factors in shaping firms' investment decisions in response to AI innovations. In the longer-term, the change in the growth path of intangible capital were similar in response to both the widespread availability of GenAI and deep learning. Overall, our findings indicate that the GenAI wave has had a more pronounced impact on intangible capital accumulation in the four ASEAN+3 economies than the preceding AI-related innovation in the mid-2010s.

Several studies have examined the formation of intangible capital in major ASEAN+3 economies, including works by Chun and Nadiri (2016), Fukao et al. (2009), and Hao and Wu (2021). These studies primarily assess the contribution of intangibles to productivity growth at the aggregate level and estimate intangible capital stocks using survey data. Our research extends this body of literature by providing consistent estimates of intangible capital at the firm level across the four ASEAN+3 AEs. By exploring the evolution and determinants of intangible capital investment in these economies, our study offers valuable insights for policymakers in the ASEAN+3 region, enabling them to better tailor their economic strategies to leverage intangible capital for sustainable growth.

The rest of the paper is organized as follows. Section 2 describes our data sources and the methodology used for estimating intangible capital as well as its trends in the four ASEAN+3 economies and the US over time. Section 3 presents the econometric analysis of the impact of AI advancement on intangible capital accumulation in these economies. Section 4 concludes with a discussion on the policy implications of our findings.

2. Data and Trends

Our primary data source is the Standard and Poor’s (S&P) Capital IQ Pro (CIQ) database, which is the expanded and updated iteration of the legacy Compustat database. We compile firm-level financial statements information for both public and private firms across the four ASEAN+3 AEs, namely, Hong Kong, Japan, Singapore, and South Korea, as well as the US. Our main analysis centers on the period from 2012 to 2023, although data from 2000 onwards were used to estimate firms' intangible capital. We exclude firms with missing or non-positive book value of assets or sales. Additionally, economy-level real GDP growth, reported by national authorities and extracted via CEIC, were also included later in the econometric analysis to account for background macroeconomic conditions that may also affect the accumulation of intangible capital. Table 1 describes the full list of variables included in the paper.

Table 1: Variables included

Variable	Source	Explanation
Research and development expenditure (R&D)	S&P CIQ	Input for knowledge capital
Selling, general and administrative expenses (SG&A)	S&P CIQ	Input for organisational capital
Net property, plant and equipment (Net PP&E)	S&P CIQ	Proxy for physical capital
Knowledge capital	Computed	Computed from R&D
Organisational capital	Computed	Computed from SG&A
Intangible capital	Computed	Sum of knowledge and organisational capital
Real gross domestic product (GDP) growth	CEIC	Proxy for overall macroeconomic conditions
Market capitalisation	S&P CIQ	Market valuation

The accounting treatment of intangible capital is governed by International Accounting Standard (IAS) 38, which stipulates that a company may only recognise intangibles an asset if it is identifiable, controlled, measurable, and if it is probable that the company will accrue future economic benefits from the asset. The International Financial Reporting Standards (IFRS) permit the capitalisation of development costs, but only under stringent conditions. In contrast, under Generally Accepted Accounting Principles (GAAP), internally generated intangibles are typically not capitalised. These accounting regulations render the valuation of intangibles from financial reports challenging, necessitating assumptions in measuring intangibles.

Our measurements of capital are standard in the literature (Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017; Van Criekingen et al. 2022). We measure the replacement cost of physical capital, C^{phy}, as the book value of property, plant, and equipment. We define the replacement cost of intangible capital, denoted C^{int}, to be the firm's internally created intangible capital. To construct a proxy of the replacement cost, we accumulate past intangible investments, as reported on firms' income statements.

A firm develops knowledge capital by spending on R&D. We estimate a firm's knowledge capital by accumulating past R&D spending using the perpetual inventory method:

$$K_{it} = (1 - \delta_{R\&D})K_{i,t-1} + R\&D_{it} \qquad (1)$$

where K_{it} is the end-of-period stock of knowledge capital, $\delta_{R\&D}$ is its depreciation rate, and $R\&D_{it}$ is expenditures on R&D during the year. We assume $\delta_{R\&D} = 0.32$.

We assume that a fraction of a firm's SG&A expenditure represents an investment in organization capital through advertising and marketing, employee training, and information technology. We similarly use the perpetual inventory method to measure the stock of organization capital by accumulating a fraction of past SG&A spending:

$$O_{it} = (1 - \delta_{SG\&A})O_{i,t-1} + SG\&A_{it} \times \mu_{SG\&A} \qquad (2)$$

where O_{it} is the end-of-period stock of organization capital, $\delta_{SG\&A}$ is its depreciation rate, $SG\&A_{it}$ is the selling, general, and administrative expenses during the year and $\mu_{SG\&A}$ is the fraction of SG&A that is counted as organization capital expenditure. We assume $\delta_{SG\&A} = 0.2$ and $\mu_{SG\&A} = 0.28$.

A firm's intangible capital is then calculated as the sum of its knowledge and organization capital, $C_{it}^{int} = K_{it} + O_{it}$. The starting stock of either form of capital is 0 at start of our dataset in 2000 or the first instance of the firm appearing in our dataset during the period covered. Due to the way the dynamics of knowledge and organisational capital are defined in equations 1 and 2, even if there are disagreements on the initial quantitative values (at t=0), the subsequent paths from 2012 should not vary significantly.[2]

Figure 1 illustrates the trends in annual average R&D and SG&A expenditures, alongside the annual average stocks of knowledge, organizational, and intangible capital across five studied economies. We observe variations in the accumulation paths of intangible capital over time in the ASEAN+3 AEs and the US, as depicted by solid black lines. In the US (Panel A), the accumulation of intangible capital first accelerated around 2016, coinciding with the widespread adoption of deep learning technologies. This acceleration became more pronounced around 2021-22, aligning with the mainstream adoption of GenAI.

In Figure 1, the pattern of intangible capital accumulation observed in the US during the GenAI period is similarly noted in Hong Kong and Singapore (Panels B and C). However, this pattern is not evident in Japan and Korea (Panels D and E), where the average intangible capital has been either declining or remaining flat since the early 2010s. Unlike in the US, the impact of deep learning breakthroughs in 2016 is less apparent in Hong Kong and Singapore, suggesting that the increase in intangible capital formation driven by deep learning may be specific to the United States.

By segregating intangible capital into knowledge capital (blue solid lines) and organizational capital (red solid lines), Figure 1 further demonstrates that the acceleration of intangible capital formation in the US, Hong Kong, and Singapore since the GenAI breakthrough in 2021 is primarily driven by the accumulation of knowledge capital, rather than organizational capital. Notably, the stocks of knowledge capital in the US and Singapore have surpassed those of organizational capital from 2021 onward. The stock of knowledge capital in Hong Kong also increased by 351% (compared to 120% in the US and 104% in Singapore) from 2012 to 2023, which may reflect the reconfiguration in the global and regional trade value chain, as well as economy-specific policies to promote innovation and technology. Conversely, the relative proportions of knowledge capital and organizational capital in Japan and

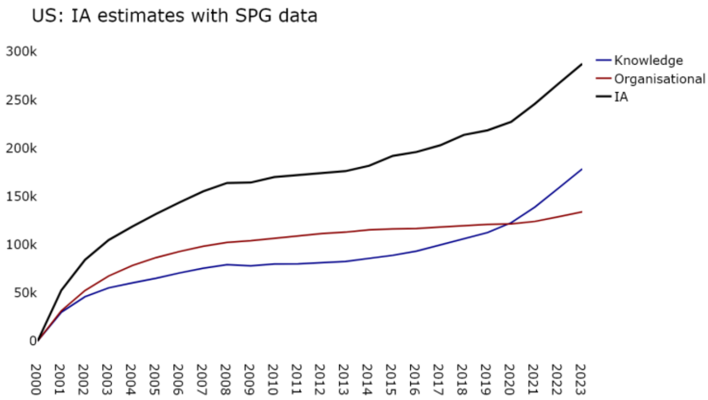
[2] One US dollar worth of knowledge and organization capital in 2000 would be depreciated to US 5.07 cents and 6.87 cents, respectively, by 2012. At a minimum, we can interpret our estimates in terms of trend.

South Korea have remained stable since the early 2010s. These cross-economy variations may be attributed to economy-specific factors that influence firms' investments in intangible capital and warrant further research.

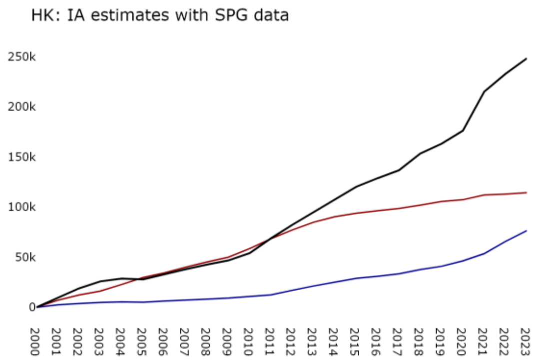
Figure A1 in the Appendix depicts the accumulation path of physical capital over time in the five economies. It is observed that intangible and physical capital are positively correlated over time. This correlation aligns with existing literature and suggests that firms choose optimal intangible and physical investment rates at the margin (Peters and Taylor, 2017). The higher volatility observed in physical capital stocks over time can be attributed to the fact that while the estimation of intangible capital is cost-based, firms are required by IAS 16 to mark the value of physical capital to fair market value.

Figure 1: Average R&D, SG&A, knowledge capital, organisational capital, and intangible capital

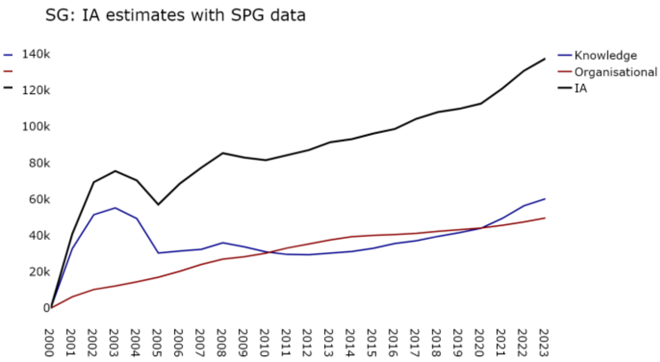
A. United States



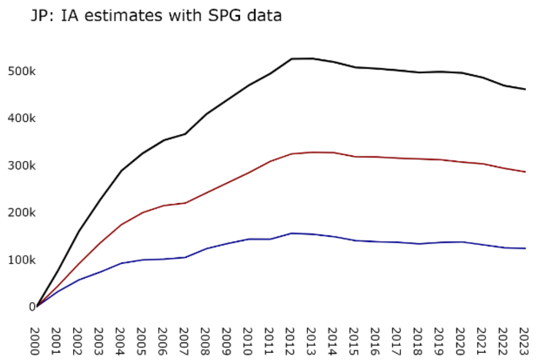
B. Hong Kong



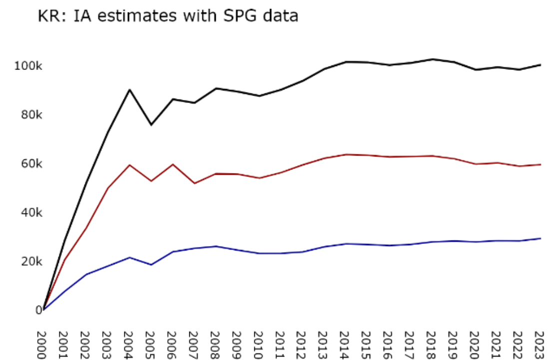
C. Singapore



D. Japan



E. South Korea



In each panel, the blue, red, and black solid lines represent the annual average stocks of knowledge, organizational, and intangible capital, respectively, of public and private firms in an economy. All variables are measured in thousands US Dollars (USD '000s).

Tables A1 to A5 provide the summary statistics of the firm-level variables in Table 1. Guided by our observation that the advancements of deep learning in 2016 and GenAI in 2021 might have stimulated intangible capital formation in some economies, we divided our full sample from 2012 into two overlapping periods. The first spans 2012 to 2019, and is segmented by 2016, the year when deep learning became widespread globally, indicated by a jump in number of academic papers on deep learning (Saputra et al., 2024; Yapıcı et al., 2019) and in the number of searches on Google for "deep learning AI" (Figure A2 in the Appendix). The second period spans 2012 to 2019, and is segmented by 2021, the year when Dall-E was first launched to the public. The first and second panels in each table present the summary statistics in the two periods, respectively.

The time coverage and segmentation of these two panels correspond to our subsequent ITS analysis. As the dataset covers both public and private firms, there is a considerable degree of heterogeneity in terms of both physical and intangible capital accumulation, despite the removal of firms with insufficient data coverage. This variation is also evident in the variation in market capitalization, which later informs our decision to include firm fixed effects in our econometric analysis to account for the non-trivial between-firm heterogeneity.

3. Econometric Analysis

If major AI innovations are introduced concurrently to the global economy, how should one estimate the impact of AI on intangible capital accumulation? Conceptually, any resultant change in a firm's accumulation path comprises two components: (i) a direct effect from the adoption or intent to adopt the technology, and (ii) an indirect effect or spillovers from other parties that have adopted the technology. Consequently, comparing firms with varying degrees of exposure to the technology will likely underestimate the effect of AI, as this approach discounts the indirect effect entirely or partially. In the context of a global technological shock, it is not possible to identify true control groups, which precludes the use of a difference-in-difference research design.

The interrupted time series (ITS) methodology offers a solution to this challenge. As described by Bernal et al. (2017, 2021), the ITS methodology is increasingly being adopted in the adjacent field of epidemiology, which often lacks true control groups, a circumstance also applicable to our situation. This approach involves estimating a segmented linear regression model that captures two key components: (i) a trend shift and (ii) a slope shift associated with the global event or shock. In essence, the ITS methodology assesses the difference between the actual post-event trend and a counterfactual post-event trend derived from the pre-event trend.[3]

Our implementation of the ITS follows Bernal et al. (2017, 2021), extended to a panel data setting with a fixed effects regression model in equation (3). We regress intangible capital y_{it} on economy fixed effects α_i, a trend term t, a dummy indicating when the event of interest has taken place $1\{post_t\}$, an interaction term between the post-event dummy and the time elapsed since the event, as well as both firm- and economy-level controls in $\boldsymbol{X_{it}}$. ε_{it} is the error term. y_{it} is expressed as the percentage difference in intangible capital relative to its level during the event year t_{event}. For example, $y_{i,2023}$=26 means that intangible capital for firm i in year 2023 were 26% higher than in 2021. This allows us to better compare changes in intangible capital in response to both shocks between firms that may differ in scale. Essentially, the ITS model segments the trends in the pre- and post-event periods, and compares them in β_3, which yields the slope difference in the post-event period relative to the pre-event period. β_2, on the other hand, represents the level shift that is associated with the onset of the event at t_{event}.

$$y_{it} = \alpha_i + \beta_1 t + \beta_2 \cdot 1\{post_t\} + \beta_3 (t - t_{event}) \cdot 1\{post_t\} + \boldsymbol{X_{it}\beta_4} + \varepsilon_{it} \qquad (3)$$

To estimate the effects of deep learning and GenAI, we restrict our dataset to the periods 2012-2019 and 2016-2023, respectively. t_{event} is assumed to be 2016 for deep learning and 2021 for Gen AI, the specifics of which are discussed in Section 1. In the deep learning case, the starting year of 2012 is chosen to avoid confounding effects from the immediate aftermath of the global financial crisis, while the ending year of

[3] Botosaru et al. (2024) discussed the evaluation of treatment effects in the absence of control groups. Schaffer et al. (2021) proposed a variant of the ITS methodology that utilizes forecasts from a time series model as counterfactuals.

2019 is chosen to avoid the COVID-19 pandemic and the subsequent global rollout of GenAI tools. The GenAI case overlaps with the COVID-19 pandemic but we attempt to address this consideration by including economy-level real GDP growth in $\boldsymbol{X_{it}}$ to control for overall macroeconomic conditions.

Tables 2 and 3 present the estimates of Equation 3 for the GenAI (2016-23; shock in 2021) and deep learning (2012-19; shock in 2016) cases, respectively. It is essential to note upfront that there may be some degree of uncertainty in the ITS estimates for some economies due to the relatively short time window at an annual frequency.

Table 2 reports an increase in the level, as well as the slope of intangible capital accumulation, as indicated by the coefficients on the event dummy and the interaction term (*Post-time x Post-event*), respectively that is associated with the introduction of GenAI globally in 2021. The β_2 estimates for the US show a statistically significant 52.25% (95% confidence interval: 46.96% to 57.52%) jump in intangible capital, followed by a 23.83% (95% CI: 21.88% to 25.78%) increase in the slope of intangible accumulation relative to its 2021 levels, as indicated by the β_3 estimates. The estimates for the four ASEAN+3 economies are also similar qualitatively, i.e., a slope shift that follows a larger level shift, with variation in the degree of statistical significance. The generalizability of our ITS estimates suggests that, in response to the recent global GenAI rollout, firms in the four selected ASEAN+3 economies and the US on average have accelerated their accumulation of intangible capital. As indicated in Figure 1, most of this acceleration is in the form of knowledge capital, although some acceleration in organizational capital is also observed.

In contrast, the estimated effects of deep learning are smaller compared to those of GenAI. In table 3, across all five economies, the level shift in intangible capital in response to the widespread availability of deep learning in 2016, as indicated by the estimates for the event dummy β_2 were smaller than in response to the GenAI rollout. However, the slope shifts in intangible capital accumulation, as indicated by the coefficient estimates on the interaction term β_3, in response to both the deep learning and GenAI rollouts were similar. In the US, Hong Kong, Japan and Korea, the slope shift terms were statistically significant, while the trend shift terms were statistically significant only in Japan and Korea. Again, this reflects some degree of uncertainty in some of the estimated parameters owing to the short time window in an annual setting. These estimates underscored that the GenAI wave was, at least from the perspective of its effects on intangible capital, orders of magnitude larger than the preceding AI-related innovation in the mid-2010s in the near-term, although the longer-term effects on intangible capital growth were potentially comparable.

Table 2: ITS estimates for 2016 to 2023 (event: 2021)

	Intercept	**GDP**	**Post-event**	**Post-time x Post-event**	**Time**
Panel A: United States					
Parameter	227.93	-3.76	52.25	23.83	-43.41
Lower bound	222.47	-4.30	46.96	21.88	-44.68
Upper bound	233.39	-3.23	57.54	25.78	-42.13
Panel B: Hong Kong					
Parameter	85.40	-0.41	15.43	8.22	-16.58
Lower bound	60.55	-1.89	-8.86	-1.44	-23.42
Upper bound	110.24	1.08	39.72	17.87	-9.74
Panel C: Singapore					
Parameter	116.70	-0.69	19.76	9.68	-21.82
Lower bound	47.75	-6.48	-69.07	-10.08	-39.06
Upper bound	185.65	5.10	108.59	29.45	-4.58
Panel D: Japan					
Parameter	101.99	-2.22	24.53	10.26	-20.28
Lower bound	89.96	-4.01	10.08	6.13	-23.89
Upper bound	114.02	-0.44	38.99	14.39	-16.66
Panel E: South Korea					
Parameter	127.63	-4.10	35.51	14.54	-24.12
Lower bound	108.23	-6.65	18.90	9.05	-28.15
Upper bound	147.03	-1.55	52.12	20.03	-20.09

Note: The lower and upper bounds refer to the 95% confidence intervals.

Table 3: ITS estimates for 2012 to 2019 (event: 2016)

	Intercept	GDP	Post-event	Post-time x Post-event	Time
Panel A: United States					
Parameter	143.79	2.61	18.59	26.53	-33.85
Lower bound	104.94	-17.62	-7.39	18.80	-39.78
Upper bound	182.63	22.84	44.57	34.27	-27.92
Panel B: Hong Kong					
Parameter	58.29	-1.26	3.89	12.70	-11.97
Lower bound	34.25	-6.28	-9.83	4.65	-18.11
Upper bound	82.34	3.76	17.62	20.74	-5.84
Panel C: Singapore					
Parameter	52.22	-1.12	7.85	5.47	-11.07
Lower bound	-29.12	-12.37	-23.62	-7.54	-25.72
Upper bound	133.57	10.13	39.31	18.48	3.58
Panel D: Japan					
Parameter	69.43	-0.55	6.81	10.12	-15.30
Lower bound	61.89	-2.18	2.81	7.58	-17.40
Upper bound	76.98	1.09	10.82	12.65	-13.20
Panel E: South Korea					
Parameter	102.66	-7.18	8.61	12.11	-17.67
Lower bound	77.93	-14.32	2.62	9.18	-20.09
Upper bound	127.38	-0.05	14.60	15.03	-15.25

Note: The lower and upper bounds refer to the 95% confidence intervals.

There are several limitations in our econometric analysis. First, there may be other macro-level confounders, as well as country-specific factors that may distort the path of intangible capital. To address this, our analysis controlled for real GDP growth, which directly accounts for the booms and busts experienced throughout our sample period, including the COVID-19 pandemic, as well as various geopolitical and trade events in the late-2010s.

Second, the time coverage of our analysis is relatively short. However, the limitations that may have instead arisen from a longer time series could have been greater in our setting, due to the presence of other major economic shocks, such as the Global Financial Crisis, as well as multiple AI-related shocks may have been greater. Other papers that deployed similar methodology also often utilised annual data with short time coverage specifically to avoid preceding or successive shocks that are irrelevant to the event of interest.

Third, our analysis lacks a control group, which precludes an implementation of DiD due to the global nature of both the deep learning and GenAI shocks. The ITS approach is precisely suitable for such a circumstance. While synthetic controls are technically feasible, they may underestimate the effect of global shocks, such as the deep learning and GenAI shocks, by potentially precluding the indirect effects of AI adoption by other firms.

4. Conclusion

Intangible capital has been the subject of extensive and intensive study in the field of economics, shedding light on persistent macroeconomic trends such as the deceleration of total productivity growth, the diminishing share of labor income, weak physical capital investment, and the escalation of firm valuations (Crouzet et al., 2022). Utilizing the US as a benchmark, this paper has provided two consistent points on the evolution and characteristics of intangible capital in four ASEAN+3 economies. First, the near-term effects of the advent of GenAI in 2021 on the level of intangible capital were larger than that of deep learning in 2016. Second, the longer-term effects on the growth of intangible capital were similar in both cases of AI innovation. Our findings suggest that these economies may follow distinct paths in the accumulation of intangible capital, which merits further investigation.

Recent advancements in GenAI, marked by the introduction of technologies such as Dall-E and ChatGPT in 2021/2022, are widely recognized as a significant technological breakthrough. Early adoptions and macroeconomic projections suggest that GenAI could substantially enhance productivity, potentially contributing up to a 7% increase in global GDP over the next decade (Brynjolfsson et al., 2023; Briggs and Kodnani, 2023). Over a brief period, our analysis provides suggestive evidence that the advent of GenAI has catalyzed an acceleration in the accumulation of intangible capital in the US, Hong Kong, Japan, Singapore, and South Korea since 2021, primarily driven by the accumulation of knowledge capital.

Over the past century, experiences with transformative technologies such as the steam engine, electricity, the internal combustion engine, and computers indicate that the diffusion of new technologies typically begins with a period of relatively slow productivity growth, followed by significant accelerations (Brynjolfsson et al., 2009). A similar trajectory is likely with the diffusion of GenAI. To capitalize on the potential benefits of AI transformation, policymakers in the ASEAN+3 economies are encouraged to assess their current standing in terms of intangible capital and to develop strategies that support investments in intangible capital, thereby facilitating the AI transformation within their respective economies.

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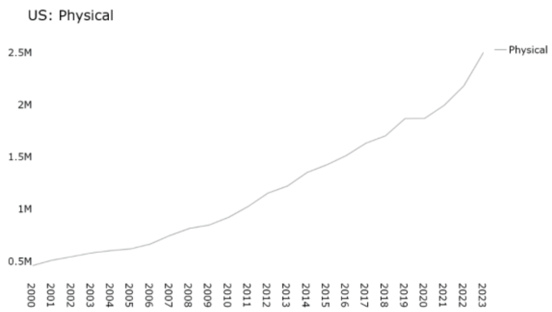
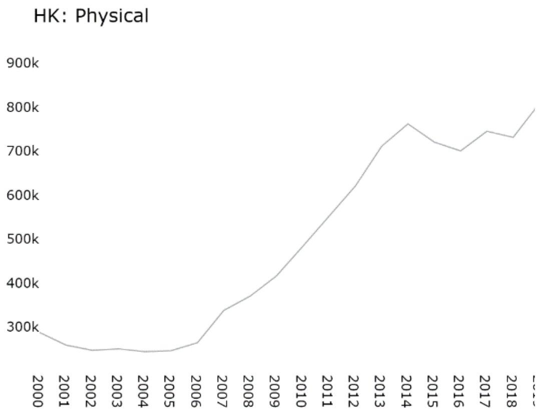
Appendix

Figure A1: Physical capital accumulation

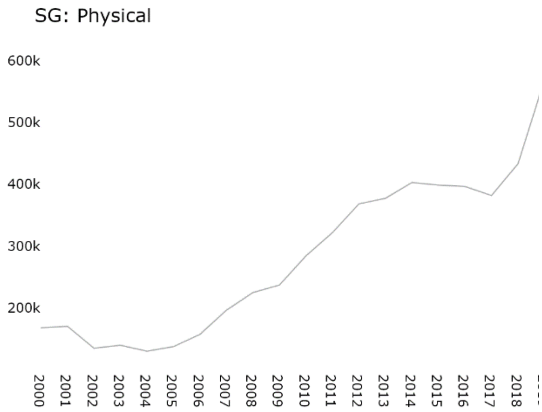
A. United States



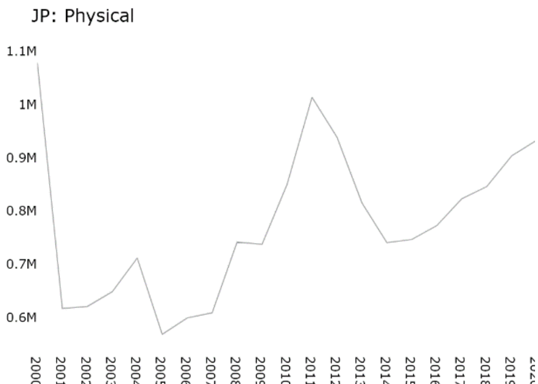
B. Hong Kong



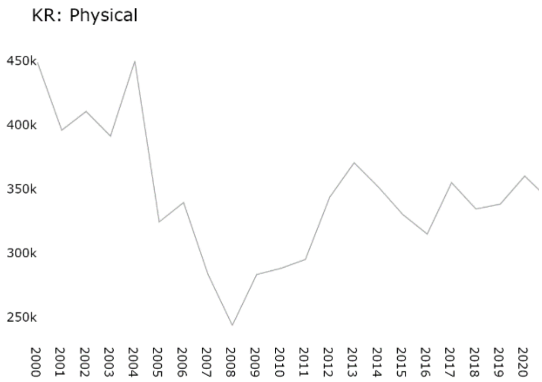
C. Singapore



D. Japan



E. South Korea



In each panel, the vertical axis represents the annual average stock of physical capital of public and private firms in an economy, measured in US Dollars.

Figure A2: Google trends index for searches of "deep learning AI" worldwide

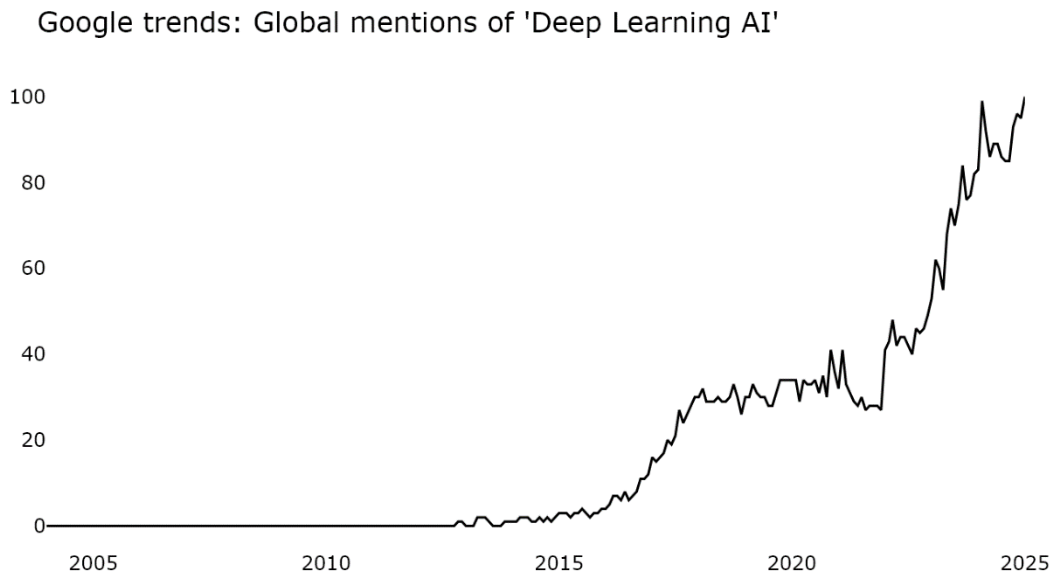


Table A1: Summary statistics for the United States

A. 2012 to 2019 (breakpoint: 2016)

	US: 2012 to 2019													
	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016
mean	345297.33	320847.35	192470.18	159860.42	202779.06	191817.24	68933.2	54413.5	152934.73	148668.82	3918610.49	3286169.64	4419.25	4421.17
std	2451166.24	2235728.57	1893869.2	1257125.86	2021738.88	1819916.36	795046.8	450305.98	1627373.99	1513058.37	12573629.8	11147817.36	57126.02	57128.4
min	0.0	0.0	-13.35	-62.43	-10279.37	-6331.8	-355.0	-2456.18	-22000.0	-1485000.0	-3671981.0	0.0	0.0	0.0
10%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6069.84	4068.0	8.96	8.96
25%	68.57	175.5	0.95	4.23	20.9	49.83	0.0	0.0	0.0	0.0	34096.75	25651.06	32.63	32.68
50%	1189.17	3056.02	84.56	363.36	646.05	1447.83	0.0	0.0	0.0	0.0	310204.5	228589.0	132.7	132.7
75%	19497.4	32000.58	3089.87	8492.09	13945.2	20781.84	0.0	0.0	0.0	1474.49	2354750.0	1907237.35	752.3	745.93
90%	288561.79	299751.69	86873.57	101051.01	165799.85	173547.32	16580.7	27663.2	87647.0	113046.5	9520716.0	8499000.0	4141.86	4135.65
max	61203276.33	53488602.68	76287326.94	25700688.56	135041237.47	115312967.26	35931000.0	12540000.0	107891000.0	97041000.0	259651000.0	252668000.0	2033984.4	2033984.4
N(firms)	1737.0	1737.0	1776.0	1776.0	11854.0	11854.0	1776.0	1776.0	11854.0	11854.0	1914.0	1914.0	4367.0	4367.0

B. 2016 to 2023 (breakpoint: 2021)

	US: 2016 to 2023													
	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021
mean	388101.03	348722.4	281006.58	199437.89	222371.44	204365.13	109186.84	72020.84	176524.05	154156.01	5034709.78	4042109.16	4422.35	4418.11
std	2913048.87	2490037.24	4158680.22	2084211.71	2361562.51	2054838.83	1849693.35	880851.63	1969886.25	1660659.93	15529338.0	12868239.88	57128.57	57125.27
min	0.0	0.0	-1.94	-13.35	-432468.09	-13005.44	-3.0	-1118.11	-2195315.0	-26000.0	-5223000.0	-3671981.0	0.0	0.0
10%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8757.5	6552.5	8.97	8.96
25%	24.3	60.12	0.18	0.76	7.8	18.71	0.0	0.0	0.0	0.0	54311.5	36131.75	32.68	32.63
50%	411.24	1066.9	15.1	68.9	244.15	578.73	0.0	0.0	0.0	0.0	447120.5	326750.0	132.7	132.7
75%	10793.14	18397.18	748.78	2672.35	7258.05	13140.53	0.0	0.0	0.0	0.0	3065747.0	2426504.75	751.64	751.64
90%	242640.26	290048.9	51081.83	80877.94	139124.86	163869.8	5655.9	15087.2	64610.5	84453.4	11465321.6	9679400.0	4141.86	4141.86
max	70465805.68	63372219.68	191075388.69	94615382.32	157328688.95	140593629.98	85622000.0	42740000.0	130971000.0	116288000.0	276690000.0	259651000.0	2033984.4	2033984.4
N(firms)	1737.0	1737.0	1776.0	1776.0	11854.0	11854.0	1776.0	1776.0	11854.0	11854.0	1914.0	1914.0	4367.0	4367.0

Table A2: Summary statistics for Hong Kong

A. 2012 to 2019 (breakpoint: 2016)

	HK: 2012 to 2019													
	Intangible assets		**Knowledge capital**		**Organisational capital**		**R&D**		**SG&A**		**Physical capital**		**Market capitalisation**	
	Post-2016	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**
mean	354367.56	249695.16	107743.83	72380.96	162312.57	127310.52	38679.17	30471.99	137870.07	121998.04	1722277.13	1565116.04	2407.4	2145.66
std	1164056.58	734863.42	457749.38	270218.58	720653.65	591714.27	165982.23	133330.09	650529.39	549012.15	7793686.84	7595673.36	11270.52	11571.27
min	0.0	0.0	-0.68	-3.17	0.0	0.0	0.0	0.0	-2194.31	-4016.69	0.46	2.71	0.0	0.0
10%	121.71	297.15	0.0	0.0	406.37	803.49	0.0	0.0	0.0	0.0	1786.62	1388.73	35.08	28.44
25%	2473.21	3778.68	2.93	13.68	4628.55	4709.21	0.0	0.0	1236.16	1985.95	18904.79	16253.87	75.95	62.98
50%	8898.25	11102.58	328.58	724.32	17563.4	15363.16	0.0	0.0	11585.25	11079.18	96007.69	78932.39	210.35	163.21
75%	94823.25	106802.35	17271.05	15468.78	65402.63	52868.03	5320.63	4358.07	53562.59	49713.43	551721.77	414925.16	787.8	606.22
90%	963465.95	629246.68	189153.07	173939.49	258719.66	187841.59	62095.1	55257.07	203470.43	188328.8	2763851.84	2094458.72	3776.45	3268.0
max	9495413.99	6883068.19	3844854.67	2934331.99	13402291.83	11042738.06	1374745.0	1563997.0	11620431.87	9724289.35	117353114.36	112750096.62	236037.78	259814.61
N(firms)	67.0	67.0	68.0	68.0	693.0	693.0	68.0	68.0	693.0	693.0	384.0	384.0	524.0	524.0

B. 2016 to 2023 (breakpoint: 2021)

	HK: 2016 to 2023													
	Intangible assets		**Knowledge capital**		**Organisational capital**		**R&D**		**SG&A**		**Physical capital**		**Market capitalisation**	
	Post-2021	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**
mean	477499.22	366481.91	161468.23	112614.75	186508.21	165282.18	60936.03	41670.16	144311.99	137763.67	2002914.14	1764245.78	2051.74	2342.9
std	1670080.23	1209266.35	677171.1	471006.53	855874.12	736845.27	266414.31	173065.78	714963.52	654567.07	9002831.59	7993222.71	9065.84	10823.0
min	0.0	0.0	-0.1	-0.68	0.0	0.0	0.0	-158.46	-133.74	-2194.31	0.0	0.46	0.0	0.0
10%	42.43	113.94	0.0	0.0	169.67	376.87	0.0	0.0	0.0	0.0	2558.72	1932.98	13.31	28.35
25%	838.96	2222.3	0.6	2.65	3723.37	4568.32	0.0	0.0	0.0	709.25	21463.21	21079.11	34.29	66.18
50%	7983.47	8921.67	109.27	253.91	16311.14	17447.53	0.0	0.0	6790.92	11090.9	105339.72	99428.9	111.51	189.0
75%	175250.19	111896.17	35440.63	18785.25	73649.95	66562.28	4362.04	5717.33	44108.79	52381.32	631179.74	567216.76	445.23	738.73
90%	752507.62	877442.52	252304.16	190850.88	273080.61	262549.79	85325.0	75501.22	182842.02	201013.96	3613417.61	2862300.8	3119.6	3591.38
max	12922213.56	10120983.07	5698622.55	3998873.17	16056883.33	14039196.97	2221522.0	1384372.0	13132044.83	11847726.81	129985989.99	129015255.95	175198.39	236037.78
N(firms)	67.0	67.0	68.0	68.0	693.0	693.0	68.0	68.0	693.0	693.0	384.0	384.0	524.0	524.0

Table A3: Summary statistics for Singapore

A. 2012 to 2019 (breakpoint: 2016)

	SG: 2016 to 2023													
	Intangible assets		**Knowledge capital**		**Organisational capital**		**R&D**		**SG&A**		**Physical capital**		**Market capitalisation**	
	Post-2021	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**
mean	576483.0	536881.41	390032.9	357911.53	94173.82	86113.62	129567.59	128823.41	74119.56	67645.07	578288.02	551135.96	1739.22	1539.09
std	1410433.54	1253157.72	1042471.42	959429.09	410397.31	329824.54	355053.85	349434.86	367641.39	293737.81	1196555.2	1250553.77	6764.77	5614.08
min	0.0	0.0	0.0	0.0	0.0	0.0	-1.45	0.0	-6537.0	-326.54	0.0	2.0	1.05	0.52
10%	492.68	1084.41	1.07	3.52	31.0	83.96	0.0	0.0	0.0	0.0	2282.63	2251.7	11.85	12.12
25%	5133.41	6020.14	51.6	170.62	557.69	1234.95	0.0	0.0	0.0	0.0	10597.62	11402.32	21.99	24.48
50%	24123.22	38849.91	2027.67	4385.1	4753.43	8213.23	0.0	68.19	0.0	1067.61	54317.22	40805.89	74.91	73.53
75%	274046.62	404971.29	49259.23	88260.02	23096.52	26726.26	13250.58	26179.61	9554.96	15524.43	447328.09	407768.34	420.38	420.77
90%	1178380.45	968231.8	754314.19	602902.59	98533.2	119081.51	267941.01	219910.67	61161.57	73376.96	2153851.56	1899257.89	2627.69	3039.71
max	6116308.71	5247978.33	4335777.63	3754885.75	4010093.79	3167662.42	1712744.7	1544979.64	3931981.35	2757960.36	6298400.0	9072929.91	63287.35	51013.4
N(firms)	21.0	21.0	21.0	21.0	332.0	332.0	21.0	21.0	332.0	332.0	113.0	113.0	173.0	173.0

B. 2016 to 2023 (breakpoint: 2021)

	SG: 2012 to 2019													
	Intangible assets		**Knowledge capital**		**Organisational capital**		**R&D**		**SG&A**		**Physical capital**		**Market capitalisation**	
	Post-2016	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**
mean	529704.21	360701.66	353305.19	232045.66	85084.91	73126.79	132779.72	89199.38	67595.01	66049.66	539917.51	513452.98	1585.92	1657.56
std	1230284.21	876954.93	950054.25	717653.42	320057.19	247111.2	361335.57	270067.49	289672.91	242159.33	1258440.61	1291829.14	5761.34	5441.07
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-326.54	-5186.36	2.0	46.79	0.52	1.56
10%	1360.42	2648.99	5.1	23.87	88.26	198.25	0.0	0.0	0.0	0.0	2159.43	3315.73	13.03	17.93
25%	6420.29	8111.73	246.12	404.67	1353.49	2678.18	0.0	0.0	0.0	0.0	11321.14	10588.53	26.12	34.47
50%	40177.91	58404.24	6230.39	11754.15	8644.89	9792.07	491.05	792.18	1412.34	5820.64	39873.9	33515.83	76.69	106.5
75%	413891.6	326830.81	90433.51	129829.64	27376.4	28988.23	27708.84	33339.28	16656.48	23954.62	392643.08	338140.21	425.05	474.15
90%	920342.83	547219.21	570677.21	336694.13	123310.45	127075.9	218801.28	147895.1	75701.21	108466.32	1815832.78	1223241.83	3150.02	3639.28
max	5247978.33	4569394.92	3754885.75	3720420.23	2994772.17	2176111.09	1544979.64	1353000.0	2757960.36	2104521.37	9072929.91	10453769.0	51013.4	47399.98
N(firms)	21.0	21.0	21.0	21.0	332.0	332.0	21.0	21.0	332.0	332.0	113.0	113.0	173.0	173.0

Table A4: Summary statistics for Japan

A. **2012 to 2019** (breakpoint: 2016)

	JP: 2012 to 2019													
	Intangible assets		**Knowledge capital**		**Organisational capital**		**R&D**		**SG&A**		**Physical capital**		**Market capitalisation**	
	Post-2016	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**
mean	1698247.53	1761951.93	627516.52	689970.38	851989.26	840001.84	197835.14	218934.23	624545.89	632177.86	1501116.76	1434403.16	2255.46	1776.69
std	6023285.52	6258826.77	2486714.63	2725538.72	2920431.61	2785510.73	821747.77	904575.61	2254873.86	2199215.13	5865964.28	6064648.48	7742.0	6711.68
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-7196938.25	0.0	128.82	91.44	0.29	0.27
10%	291.24	747.29	2.82	12.99	346.75	844.59	0.0	0.0	0.0	0.0	11928.83	12634.49	32.07	27.1
25%	4805.09	8642.66	53.61	235.64	6087.72	9922.87	0.0	0.0	0.0	0.0	49945.88	50998.75	78.38	62.83
50%	37322.04	51534.22	3835.91	5231.41	52725.31	71717.44	597.8	909.19	17045.68	25410.16	192650.46	189762.86	276.6	215.2
75%	314484.33	334598.27	67145.43	69061.02	407301.32	459735.98	19345.38	20174.62	255655.29	300354.69	629016.36	603018.48	1174.0	883.42
90%	3761689.9	3165670.37	1036899.02	1029998.27	1645299.19	1629689.03	330376.49	348289.0	1192572.79	1208201.9	3186053.04	2989800.08	4696.21	3622.73
max	61802359.38	58013304.44	28073278.01	26672701.41	35290824.84	31629612.86	9734255.1	9818121.85	27929951.0	26070825.8	87158984.88	112144975.29	185366.98	204217.98
N(firms)	370.0	370.0	371.0	371.0	910.0	910.0	371.0	371.0	910.0	910.0	356.0	356.0	1711.0	1711.0

B. **2016 to 2023** (breakpoint: 2021)

	JP: 2016 to 2023													
	Intangible assets		**Knowledge capital**		**Organisational capital**		**R&D**		**SG&A**		**Physical capital**		**Market capitalisation**	
	Post-2021	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**
mean	1661457.47	1699601.4	601808.84	630863.85	854823.97	853767.64	183733.12	201320.39	595427.2	622186.37	1489273.75	1542118.64	2508.07	2272.5
std	5782354.11	6021241.03	2408025.21	2504742.99	2984576.24	2930907.66	784334.67	838285.18	2164842.03	2242050.35	5394062.97	5960030.37	9932.97	7919.06
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-7196938.25	173.7	128.82	6.23	0.28
10%	107.83	262.84	0.53	2.29	131.92	301.05	0.0	0.0	0.0	0.0	10730.21	12191.88	29.06	31.99
25%	1775.43	4276.67	11.13	47.81	2589.46	5502.54	0.0	0.0	0.0	0.0	45861.66	50999.82	70.19	78.14
50%	28475.49	36074.12	3014.29	3828.71	42196.9	52080.72	306.66	561.92	8576.08	16486.98	175699.44	195122.21	240.81	270.21
75%	285993.88	314309.54	61677.4	67168.37	357718.73	399430.72	11574.63	18469.77	211933.61	254552.81	612891.5	636623.05	1075.66	1152.48
90%	3835637.39	3855320.83	1005078.32	1060336.85	1676396.84	1650004.71	306324.1	329810.23	1143245.75	1191808.54	3277566.29	3231771.9	4536.35	4661.13
max	61653509.8	62111299.01	25201376.06	28073278.01	36452133.74	35293035.86	10027974.27	10403428.03	27213205.21	27929951.0	86944075.8	94257463.16	230466.84	185366.98
N(firms)	370.0	370.0	371.0	371.0	910.0	910.0	371.0	371.0	910.0	910.0	356.0	356.0	1711.0	1711.0

Table A5: Summary statistics for South Korea

A. 2012 to 2019 (breakpoint: 2016)

	KR: 2012 to 2019													
	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016
mean	555598.89	481374.12	216655.53	171951.67	280497.73	251234.21	77295.52	64283.41	214677.24	214741.23	2055842.98	1788070.34	1856.35	1594.92
std	5007679.51	4036528.24	2497752.48	1877316.76	1784941.05	1533392.75	911015.53	733793.19	1390980.13	1423489.17	9827772.22	8214690.91	13772.74	9918.02
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-171.26	0.0	0.02	0.02	15.42	8.57
10%	63.21	163.32	0.31	1.28	84.44	191.9	0.0	0.0	0.0	0.0	12846.76	11805.45	41.98	26.7
25%	485.39	1215.46	5.41	20.17	791.0	1717.0	0.0	0.0	0.0	0.0	39544.19	38877.07	75.27	51.02
50%	8994.07	10260.94	173.94	483.84	11526.17	13343.24	0.0	0.0	5555.54	6222.01	187211.61	174684.92	158.15	126.78
75%	78821.57	71526.27	2918.11	4345.01	81551.43	73930.03	667.15	820.12	54503.24	55780.66	824933.72	733379.17	521.11	391.94
90%	372973.5	360156.8	37637.41	37973.86	419515.52	357857.51	11860.61	10532.99	285722.3	307292.57	2837872.51	2763826.61	2398.71	2209.27
max	88979587.22	74489951.06	47905113.9	36421582.47	41292106.04	38068368.59	17333369.44	14095791.57	34475482.51	35573420.95	136274285.62	119472022.2	289998.58	189479.91
N(firms)	317.0	317.0	319.0	319.0	724.0	724.0	319.0	319.0	724.0	724.0	327.0	327.0	359.0	359.0

B. 2016 to 2023 (breakpoint: 2021)

	KR: 2016 to 2023													
	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021
mean	616819.39	561998.71	262241.1	222662.4	297663.61	281466.5	89561.59	78900.9	228971.16	212041.17	2342199.02	2119627.04	2358.99	1860.36
std	5860325.89	5097338.59	3251397.55	2588553.88	1884168.76	1789103.07	1155069.53	939295.07	1452525.39	1370287.74	11512593.82	10155440.37	20923.74	14431.6
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-402.82	0.02	0.02	20.86	12.24
10%	25.08	58.84	0.07	0.26	32.84	76.46	0.0	0.0	0.0	0.0	13504.46	12943.45	51.47	41.8
25%	182.57	424.08	1.0	4.53	320.53	735.62	0.0	0.0	0.0	0.0	39142.23	39590.3	83.82	74.08
50%	9299.91	8931.0	52.67	148.25	11269.51	11423.99	0.0	0.0	6088.5	5513.04	195779.14	192162.71	173.62	152.84
75%	83778.48	78822.42	2891.7	2813.92	84821.03	81518.32	862.35	677.24	60873.84	54503.24	922006.03	845584.7	557.97	500.47
90%	416035.92	368236.97	45764.1	37967.25	442776.19	423068.22	16398.08	12631.84	318966.37	285891.47	3228896.08	2964726.98	2446.85	2296.53
max	102950904.02	91625667.14	60187065.82	50889565.87	42763838.2	41292106.04	21772187.43	18314088.42	32401190.7	34475482.51	145349607.11	148213417.63	465470.65	312381.16
N(firms)	317.0	317.0	319.0	319.0	724.0	724.0	319.0	319.0	724.0	724.0	327.0	327.0	359.0	359.0

The Impact of the New Round of Scientific and Technological Revolution on the Economic Development of Emerging and Developing Economies —— Observations Based on ASEAN+3 Member States

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Abstract: At present, a new round of scientific and technological revolution is accelerating its evolution, and its impacts on the economic development of emerging and developing economies, as well as on the global economic development, are in the process of quantitative accumulation. This is mainly reflected in the changes of social division of labor and business organization form, factor inputs and industrial integration, transformation of economic growth momentum, and the reshaping of the global economic pattern. The new round of scientific and technological revolution offers emerging and developing economies a rare historical opportunity to achieve catch-up development, however it also implies unprecedented pressure and challenges. It is necessary to confront the deficiencies of emerging and developing economies in terms of basic conditions and core elements of the new technological revolution, especially the capability to harness the revolution. Based on the laws of technological revolution and the reality of the economies, efforts should be made to promote a qualitative change in economic and technology governance capabilities in order to adapt to and lead the new round of scientific and technological revolution, as well as the resulting transformation in production and lifestyle.

Keywords: Technological Revolution; Economic Development; Emerging Economies; Developing Economies

In the dynamic system of human social development, the role of science and technology as a key driving factor is increasingly important. The development of science and technology promotes changes in human society from quantitative to qualitative, and social progress, in turn, drives breakthroughs in science and technology in more and more fields. In recent years, based on the digital revolution, the new technological revolution represented by Artificial Intelligence (AI), cloud computing, and big data has swept across the globe, changing the way of human production and lifestyle. With closer global connections, the impact of the new technological revolution will inevitably be extensive and systematic, and no economy will be left out. To a certain extent, scientific and technological progress is a “double-edged sword”. For some economies, the impact of the technological revolution on economic development is proactive, more capable of utilize its advantages while avoiding its disadvantages. While some economies may passively accept the technological revolution, enjoying its benefits while inevitably facing pressures and challenges in their economic and social operations. In the new round of scientific and technological revolution, different strategic choices of emerging and developing economies may result different impacts on their economic development. This requires the governments of emerging and developing economies to scientifically grasp the evolutionary laws of the technological revolution, and to formulate economic development strategies and public policies that adapt to the new round of technological revolution based on the actual conditions of their own economies.

1. What are the Main Factors Driving the Technological Revolution?

The scientific and technological revolution is a fundamental transformation of the scientific knowledge and technological innovation system, and it is the process that drives social productive forces from quantitative growth to qualitative change. Throughout history, each scientific and technological revolution has followed a trajectory from the quantitative accumulation to qualitative change, and this quantitative accumulation primarily stems from social demand, economic development, and scientific discovery.

Firstly, social demand is the fundamental driver of the scientific and technological revolution. Demand is the ultimate motivation for innovation, and continuously meeting the growing and evolving social needs is the ultimate purpose of human technological progress. Engels once said, "Once society has a technological need, such a need will drive science forward more than ten universities can".[1] The accumulation of social demands stimulates human curiosity and the desire for exploration and discovery, which in turn promotes the accumulation of science and technology. When this accumulation reaches a certain level and specific conditions are met, it will trigger a revolutionary change in the scientific and technological system.

Secondly, the quantitative accumulation of economic development is a prerequisite for the scientific and technological revolution. Economic development generates new and increasingly larger social demands. The accumulation of economic development implies the accumulation of social demands. When such accumulation reaches a certain degree and meet certain conditions, it will lead to a qualitative change in the supply of science and technology. On the other hands, the scientific and technological revolution also requires strong material condition. Therefore, the technological revolution often occurs in the countries with the highest level of development at the time. Only the countries with the highest development level have the greatest accumulation of social demand and the best material conditions to guarantee the technological revolution. Then the technological revolution spreads to other countries and regions in a "flying geese pattern" according to their level of economic development.

Thirdly, the accumulation of scientific discoveries is the engine of the technological revolution. The scientific revolution and the technological revolution do not occur simultaneously. The scientific revolution precedes the technological revolution, and the time interval between the two is shortening. It is the quantitative accumulation of

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[1] Marx K., Engels F. Selected Works of Marx and Engels: Volume 4[M]. Beijing: People’s Publishing House, 1995, P.732.

scientific discoveries leads to a qualitative revolution, which in turn triggers a leap in technological innovation.

2. The Main Impacts of the New Round of Scientific and Technological Revolution on the Economic Development of Emerging and Developing Economies

The general law of the emergence and impact of the scientific and technological revolution is that social demands promote the qualitative change in the scientific knowledge system, triggering the technological revolution, which in turn drive the industrial revolution, and finally the balance between a higher level of industrial development and social demands leads to a qualitative transformation in human production and lifestyle. The new round of scientific and technological revolution will inevitably bring about another qualitative transformation in production and lifestyle, but at present, it is still in the process of quantitative accumulation. From the perspective of developing economies represented by China, the impacts of the new technological revolution on economic development during its quantitative accumulation phase are mainly reflected in multiple aspects, such as business organization form, industrial development, economic structure, as well as the reshaping of the global economic pattern.

(1) The Openness of Social Division of Labor and the Platformization of business Organization Form

Under the influence of the new round of scientific and technological revolution, the social division of labor has become increasingly unstable. High levels of informatization and intelligence has led to a more rapid update of concepts and knowledge. Specialized knowledge is no longer a barrier, the ability to absorb and apply knowledge has become more important. This means that the cultivation of basic scientific knowledge, as well as the concepts and abilities built upon it, are of greater importance to the citizens of future society, posing a significant challenge to the traditional education system. The increasingly openness of social division of labor also creates conditions for the platformization of business organization form. More and more businesses are no longer assembly lines for the production of specific goods or services, but rather platforms that provide resource support. In 2023, the total revenue of the top 10 listed platform companies in China by market value reached 3.6 trillion yuan, with a total net profit of 385.44 billion yuan[2].

(2) Convergence of Factor Inputs and Integration of Industrial Development.

The new round of scientific and technological revolution will shape a brand-new mode of production and process, leading to an increasing convergence in the proportion of factor inputs at different stages of the industrial chains and value chains. The impact of digitalization and intelligence on the costs of various stages is growing, with the role of labor in production gradually declining and being largely replaced by machines. The traditional comparative advantages of factor endowments between countries and regions are weakening. While promoting the formation of emerging industries, new technologies also penetrate into traditional industrial sectors, accelerating the integration between and within industries, and blurring the boundaries between industries. Based on the gradual integration with informatization, traditional industrialization has developed a new trend of further integration with intelligence, promoting a high degree of integration among different industrial categories, regions, various sizes of businesses, and upstream and downstream sectors, thereby forming networked economies of scale. Taking JD.com Group, one of China’s leading platform companies, as an example. Its main business is online retail, it not only sells self-operated products but also provides a retail platform for numerous businesses. While offering goods to consumers, it also provides logistics services for businesses and consumers. Furthermore, it extends upstream into manufacturing with the "JD

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[2] China Academy of Information and Communications Technology (CAICT). Observation on the Development of the Platform Economy 2024[R]. Beijing: CAICT, 2024.

Manufacture" brand, forming a vast network that covers production, distribution and consumption. These have made JD become a representative of China's “new-type entity enterprise.”

(3) Spur New Drivers of Economic Growth and Catalyze Economic Structural Contradictions.

The industrial revolution triggered by the scientific and technological revolution directly promotes the improvement of total factor productivity, which will significantly enhance the potential economic growth rate. In recent years, the comparative advantages in economic development of some emerging and developing economies have weakened, the dividends of reform and opening-up, as well as the demographic dividend, have somewhat diminished, leading to a trend of decline in the potential economic growth rate. Accelerating the breakthrough and application of new technologies can offset the impact of an aging population. Under the circumstances where the growth bottlenecks for traditional labor productivity, land productivity, and capital productivity are becoming more pronounced, the old drivers of economic growth are bound to weaken. The formation of new drivers of growth is not an overnight task, and the transition between old and new drivers will inevitably hinder the smooth operation of the national economy. Breaking through the bottleneck of the transition between old and new drivers depends on the extent to which emerging and developing economies lead, follow, and diffuse in the new technological revolution. On the other hands, the structural contradictions and institutional constraints in the economic operation of emerging and developing economies not only restrict the penetration process of technological revolution, but also change with the qualitative changes of production and lifestyle, leading to the intensification or upgrading of structural contradictions.

(4) Reshape the Global Economic Pattern and Strengthen the "Catch-up" Development Barriers.

The role of scientific and technological production factors has become more prominent, making it more difficult for less developed countries or regions to achieve "catch-up" development relying on the comparative advantages in factor endowments. The inequality distribution among individuals, groups, regions, and even countries is more difficult to bridge. Under the conditions of informatization, networking and intelligence, the "winner-takes-all" feature in economic operation becomes more obvious. Once a specific economy or enterprise occupies an oligopolistic position, the latecomers essentially lose their opportunities. Data from the United Nations Conference on Trade and Development's (UNCTAD) *Digital Economy Report 2021* shows that China and the United States account for 50% of the world’s hyperscale data centers, 70% of the top AI researchers, and 94% of the financing for AI startups. China, as a "chaser", still has a noticeable gap with the United States.

3.Typical Facts of the Impact of the New Round of Scientific and Technological Revolution on the Economic Development of Emerging and Developing Economies

The new round of scientific and technological revolution has reshaped the global innovation landscape. Many emerging and developing economies, including China, have proactively seized the opportunities of industrial transformation led by digital technology, achieving a crucial shift from followers to leaders. After decades of catching up, emerging and developing economies like China have become global innovation leaders in many fields, significantly enhancing their position in the global innovation landscape. Scientific and Technological (S&T) clusters are no longer confined to traditional technology powerhouses. The new generation of technological revolution is rapidly integrating into various application scenarios, with new economies, new business formats, and new models emerging continuously. The global industrial and supply chain is undergoing profound changes.

(1) Driven by the New Round of Scientific and Technological Revolution, Asian Emerging Markets have become a Key Force in Promoting Global Economic Recovery

Asian Emerging markets are showing strong development momentum, and the new round of scientific and technological revolution has become a key force in driving global economic recovery. According to the World Bank's forecast, the average economic growth rate of advanced economies in 2024 is only 1.7%, with the United States and the Euro area at 2.8% and 0.7% respectively, while the growth in the East Asia and Pacific region reaches 4.1%, with China and Indonesia at 4.9% and 5.0% respectively[3]. Asian emerging market economies have become an important force in driving global economic growth. Among them, the digital economy has demonstrated strong resilience and vitality, bringing new growth drivers to the global economy and providing important support for global economic recovery[4]. This is because the ASEAN+3 region boasts a number of the world's most innovative and technologically productive S&T clusters, with seven of the world's top ten S&T clusters located in the ASEAN+3 region. Tokyo-Yokohama (Japan) is the world's largest S&T cluster. The second to fifth places are Shenzhen-Hong Kong-Guangzhou (China, Hong Kong), Beijing (China), Seoul (Republic of Korea), and Shanghai-Suzhou (China) in sequence. Subsequently, Osaka-Kobe-Kyoto (Japan) and Nanjing (China) rank the 7th and 9th respectively (Table 1). Innovation is the driving force for sustained economic growth, and the new technological revolution will reshape the economic development of the ASEAN+3 region, creating more opportunities for economic growth.

Table 1 TOP 10 Science and Technology (S&T) cluster, 2024

RANK	CLUSTER NAME	ECONOMY	PREVIOUS RANK(2023)	CHANGE
1	Tokyo-Yokohama	Japan	1	-
2	Shenzhen-Hong Kong-Guangzhou	China, Hong Kong	2	-

3 World Bank. Global Economic Prospects, January 2025 [R]. Washington, DC: World Bank, 2025.

4 China Academy of Information and Communications Technology (CAICT). Global Digital Economy Development Research Report 2024[R]. Beijing: CAICT, 2025.

3	Beijing	China	4	+1
4	Seoul	Rep. of Korea	3	-1
5	Shanghai-Suzhou	China	5	-
6	San Jose-San Francisco, CA	United States	6	-
7	Osaka-Kobe-Kyoto	Japan	7	-
8	Boston-Cambridge, MA	United States	8	-
9	Nanjing	China	12	+3
10	San Diego, CA	United States	9	-1

Source: Global Innovation Index 2024, WIPO

(2) Address the Impact of Aging Population and Activate New Economic Growth Drivers

In recent years, the ASEAN+3 region has been facing an increasingly severe issue of aging population, with the demographic dividend continuously diminishing and comparative advantage gradually weakening. Although rapid technological progress may lead to short-term job losses, as the working-age population shrinks, the shift towards automation, robotics, and artificial intelligence can supplement human capital in an aging environment, slowing down the decay rate of the quantitative demographic dividend. The ASEAN+3 region has been the world's largest industrial robot market. In 2023, China, Japan, Republic of Korea and Thailand accounted for 66% of the global industrial robot installations. Among them, China has been the world's largest industrial robot market since 2013 and accounted for 51% of total installations 2023. Japan and Republic of Korea ranked the 2^{nd} and 4^{th}, accounted for 9% and 6% of global robot installations respectively in 2023. Thailand ranked the 15^{th} and accounted for 1% of the overall total (Figure 1).

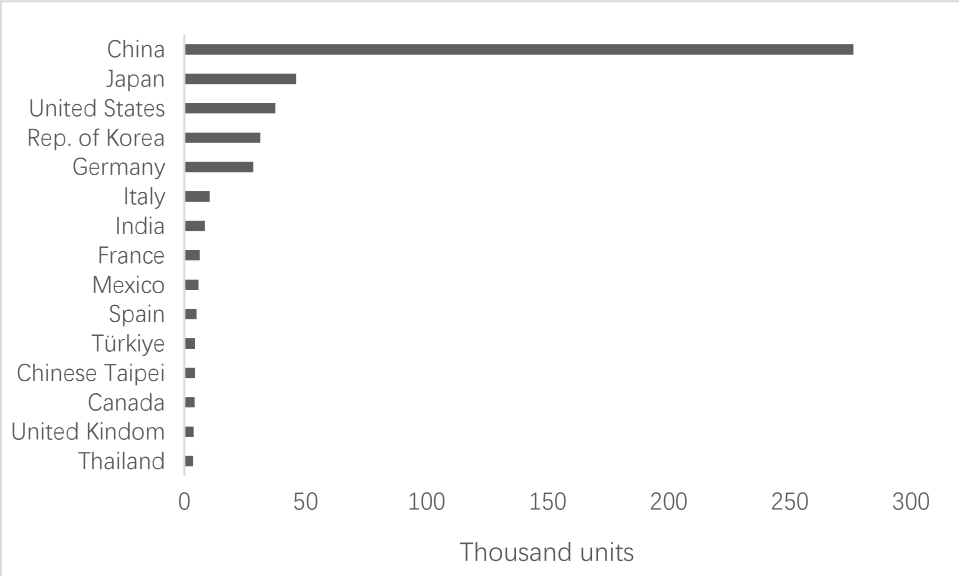

Figure 1 Annual installations of industrial robots: 15 largest markets, 2023

Source: International Federation of Robotics

Most of these industrial robots are utilized in manufacturing industries such as automotive industry, electrical/electronics industry, metal and machinery industry, and primarily for physically demanding tasks such as handling and welding. In 2023, the global average robot density in the manufacturing industry was 162 robots per 10,000 employees. While Asia's average robot density was 182 units per 10,000 employees which grew by 13% CAGR from 2018 to 2023, far outpacing other regions[5]. Moreover, technological progress has also changed the employment patterns under the traditional industrial economy, breaking the spatial and temporal constraints of employment, making employment forms and content more flexible and diversified, and providing more employment opportunities for the elderly workforce. In the face of the increasingly severe population aging today, technologies that can save labor costs, make up for labor shortages, and improve labor productivity will become increasingly important.

With the acceleration of the aging process, the silver economy is gradually becoming a new economic growth driver. Taking China as an example, in 2023, the size of China's silver economy was approximately 7 trillion yuan, accounting for 6% of GDP. By 2035,

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5 Müller, Christopher. World Robotics 2024 - Industrial Robots[R]. Frankfurt: VDMA Services GmbH, 2024.

the size of China's silver economy is expected to reach 30 trillion yuan, accounting for 10% of GDP[6]. The silver economy encompasses multiple fields such as elderly care, healthcare, medical care, culture, and tourism. With the continuous increase in the number of elderly people, the silver economy will experience explosive growth. The integration of technologies such as machine learning and artificial intelligence with the silver economy will inject new growth momentum into the economy. The future of health care will be increasingly data-driven, helping people better monitor their health conditions, diagnose diseases, and formulate treatment plans. Data-driven development will improve the accessibility, quality and efficiency of healthcare services. Compared with advanced economies, although the digital healthcare industry in the ASEAN+3 region started relatively later, due to its massive user base, the development potential of digital healthcare industry is significant (Figure 2).

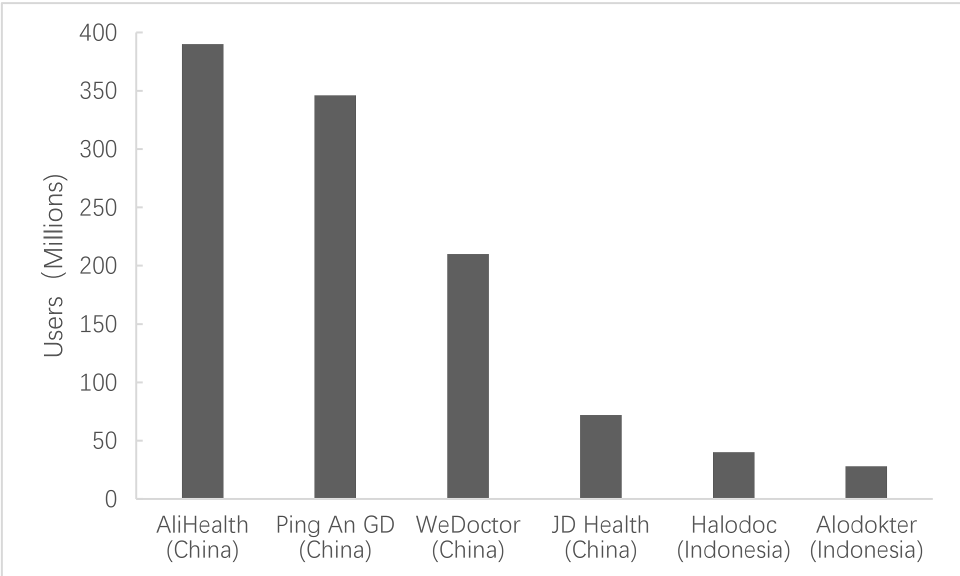

Figure 2 Top 5: Global Leading Digital Health Platforms in ASEAN+3

Source: AMRO(2024), as of January 2023

(3) Promote the Transformation of Business Organization Form and Concentration of Market and Profit

The new round of scientific and technological revolution has not only created new

6 Xu, J. Annual Report on the Development of Silver Economy in China 2024 [M]. Beijing: Social Sciences Academic Press, 2024.

business models and changed people's lifestyles, but has also propelled a major transformation in the business organization form. Benefiting from economies of scale and network effects, new digital platforms emerge continuously so markets tend to concentrate, ultimately leaving a small number of very large players in many frontier industries (Table 2). This market concentration could increase inequalities within sectors, between firms, and between capital and labour. In a market environment with fewer competitors, it is easier for few dominant companies to collude tacitly, and readily forming oligopoly. As a result, these few companies abuse their market dominance and continuously accumulate abnormal profits.

Table 2 Top frontier technology providers

AI	IoT	Big data	Blockchain	5G
Alphabet	Alphabet	Alphabet	Alibaba	Ericsson
Amazon	Amazon	Amazon Web Services	Amazon Web Services	Huawei (network)
Apple	Cisco	Dell Technologies	IBM	Nokia
IBM	IBM	HP Enterprise	Microsoft	ZTE
Microsoft	Microsoft	IBM	Oracle	Huawei (chip)
	Oracle	Microsoft	SAP	Intel
	PTC	Oracle		MediaTek
	Salesforce	SAP		Qualcomm
	SAP	Splunk		Samsung Electronics
		Teradata		
3D printing	**Robotics**	**Drones**	**Gene editing**	**Nanotechnology**
3D Systems	ABB	3D Robotics	CRISPR Therapeutics	BASF
ExOne Company	FANUC	DJI Innovations	Editas Medicine	Apeel Sciences
HP	KUKA	Parrot	Horizon Discovery Group	Agilent
Stratasys	Mitsubishi Electric	Yuneec	Intellia Therapeutics	Samsung Electronics
	Yaskawa	Boeing	Precision BioSciences	Intel
	Hanson Robotics	Lockheed Martin	Sangamo Therapeutics	

Pal Robotics	Northrop Grumman
Robotis	
Softbank Robotics	
Alphabet/Waymo	
Aptiv	
GM	
Tesla	

Source: UNCTAD (2021b)

(4) Reshape the Global Trade Landscape, Strengthen Trade with Neighbors and International Cooperation

Against the backdrop of the ongoing restructuring of the global trade landscape, the new round of scientific and technological revolution brings more opportunities for the trade in the ASEAN+3 region, continuously enhancing the resilience and flexibility of industrial and supply chains. Within the region, Singapore, Republic of Korea, and Hong Kong are considered global leaders in the application of emerging and frontier technologies in the industrial sector (Table 3). Taking the ICT products as an example, the global ICT product trade network presents a three-tier pattern of "China-US-Europe", with the Asian region being the largest cluster, forming a single-core network structure with China as the core node. Data from UN Comtrade shows that, in 2023, the export trade volume of ICT products between China and other countries and regions such as India, Vietnam, Republic of Korea, Japan, Malaysia and etc. all exceeded 20 billion US dollars, significantly strengthening the trade with neighbors. Within this cluster, China is the most important core node in the trade network in terms of both trade volume and trade connections, while Japan, Hong Kong, and Korea are secondary nodes, and countries like Singapore and Malaysia also occupy significant shares of the trade volume[7].

[7] CAICT. Global Digital Economy Development Research Report 2024[R]. Beijing: CAICT, 2025.

Table 3 Frontier Technology Readiness Index, 2022

Economy	Total score (Rank)	Index Components				
		ICT Deployment	Skills	R&D Activity	Industry Activity	Access to Finance
United States	1.00	11	18	2	16	2
Sweden	0.99	6	2	16	11	18
Singapore	0.96	7	8	17	4	17
Switzerland	0.94	21	13	12	5	5
Netherlands	0.94	4	9	15	10	31
Rep. of Korea	0.94	15	26	3	9	7
Germany	0.92	24	17	5	12	40
Finland	0.92	22	5	21	20	30
Hong Kong	0.91	9	23	29	2	1
Belgium	0.91	13	4	23	19	48

Source: UNCTAD

4. Promote a Qualitative Change in Economic and Technology Governance Capabilities to Adapt to and Lead the New Round of Scientific and Technological Revolution

The new round of scientific and technological revolution offers emerging and developing economies a rare historical opportunity for the catch-up development, however it also implies unprecedented pressure and challenges. The gap between emerging and developing economies and the “leading geese” of the technological revolution is not only reflected in aspects like the material basis, demand capacity, scientific accumulation, and factor resources of the scientific and technological revolution, but more importantly, in the differences in the concepts and abilities to harness the technological revolution and its profound impacts. In order to activate the governance efficacy in the rapid and profound transformation of production and lifestyle during the technological revolution, emerging and developing economies need to promote qualitative improvements in concepts and capabilities.

(1) Grasp the Law of Quantitative Accumulation and Qualitative Change in the

Scientific and Technological Revolution to Upgrade Economic and Technology Governance Capabilities.

The scientific and technological revolution is an inevitable transformation when social demands, economic development, and scientific progress accumulate to a certain extent. The degree of innovation, as well as its penetration in breadth and depth, are related to the preceding accumulation. Therefore, while emphasizing the mandatory technological innovation and application by government interventions, it is also necessary to make persistent efforts to create fundamental conditions for the occurrence and diffusion of the new technological revolution. First, improve demand creation and accumulation capacity. Only when new demands expand to a certain extent can trigger innovation. At a certain stage of economic development, it is necessary to implant the concept of optimizing the public demand structure and expanding the scale of private demand into reform and development, in order to form a demand-driven development model. Second, further enhance the capability for economic catch-up. It is necessary to further highlight the central position of economic development among the multiple objectives of national governance. Economic development can create conditions for the achievement of other objectives, cultivates and enhances the economic catch-up capabilities that adapt to the new technological revolution, and lay a more solid foundation for the occurrence and diffusion of the new technological revolution. Third, optimize the environmental conditions for scientific discovery and technological innovation. According to the institutions, systems, production factors and talent advantages of a specific economy, address weaknesses and eliminate drawbacks, creating a positive atmosphere across society that promote the scientific spirit, encourage exploration and discovery, and compete for innovation and progress.

(2) Accelerate the Construction of an Empowering Economic and Technology Governance Mechanism.

At present, some emerging and developing economies still exhibit distinct characteristics of traditional industrial societies in their economic and technological governance. The governance models of local governments and public departments are struggling to fulfil the needs of new technological revolution, resulting in the difficulty of coordination between economic and technology governance, and even leading to a “fallacy of composition” in governance. Therefore, it is necessary to plan reforms in inter-government relations, government function allocation, and the public service supply system based on the profound impact of the new technological revolution on production and lifestyle. This will enable high-level and modern public governance facilitating the occurrence and diffusion of new technologies, new industrial systems, and new economic growth drivers.

(3) Promote a Qualitative Upgrade of Macroeconomic Policies.

The current mainstream macroeconomic policy framework was gradually formed during the evolution of the Third Industrial Revolution after World War II and was adapted to the industrialized society. As the impact of the new round of technological revolution becomes increasingly pronounced, emerging and developing economies need to keep up with the changes, grasp the new laws of economic operation, gradually promote the optimization and innovation of macroeconomic policies. To build a new framework for macroeconomic governance, and to make the macroeconomic policy system more adaptable to a multi-objective, multi-centered and uncertain policy environment.

(4) Enhance the Resilience and Inclusiveness of Economic and Technology Governance.

The comprehensive transformation of production and lifestyle triggered by the new technological revolution implies a significant increase in uncertainties in economic operation and technological progress. There are more unpredictable factors in the fields of social division of labor, industrial integration, economic structure, and technological diffusion. The governance framework based on the relatively certain state of the traditional industrial society is no longer applicable. Therefore, the government as the governance subject, the institution as the governance rule, and the governors who implement the governance rules all need to integrate the concept of resilient governance and cultivate a more inclusive governance model. For example, in economic governance, reduce the assessment of rigid indicators and increase the examination of governance capabilities and levels; in technology governance, reduce administrative intervention and improve the mechanism for fault-tolerance and correction.

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Can an AI agent hit a moving target? *

Rui (Aruhan) Shi †

June 5, 2025

Abstract

Policymakers face challenges in understanding economic agent behavior during structural transformations, where traditional rational expectations (RE) models often struggle to capture the complexities of adaptive decision-making. This research explores how integrating artificial intelligence (AI) into a general equilibrium framework can enhance theoretical modeling by representing adaptive behaviors that integrate perspectives from neuroscience and psychology. Using a deep reinforcement learning (RL) approach, the model highlights how agents explore options, balance objectives, and adjust strategies during an economic regime change, such as an acceleration in the money supply process. Simulation results illustrate that AI agents, guided by exploration-driven learning, adapt their consumption, savings, and liquidity holding decisions in response to structural changes. These agents show a degree of convergence toward RE outcomes while retaining the flexibility to adjust under dynamic conditions, capturing behaviors that traditional models may overlook. This study provides a structured framework for analyzing bounded rationality in economies undergoing structural changes. It offers a complementary perspective to conventional approaches and highlights new avenues for research on adaptive policy design.

JEL Codes: C45, D83, D84, E31, E40, E50, E70

Keywords: expectation formation, exploration, experience, artificial intelligence, bounded rationality, deep reinforcement learning, monetary policy, regime change

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1 Introduction

The modeling of adaptive economic agents during periods of structural changes has been a topic of extensive discussion, dating back to the accelerationist debate (Sargent, 1971). The accelerationist argument, characterized by a backward-looking Phillips curve combined with adaptive expectations, suggests a plausible trade-off between inflation and unemployment. This theoretical construct posits that a government could sustain low unemployment by accelerating the money supply process. It raises the fundamental question of whether policymakers can exploit agents with naive adaptive expectations who consistently make errors.

In response to this debate, the rational expectations (RE) hypothesis was introduced, assuming that agents form model-consistent beliefs and possess a deep understanding of the economy. The RE hypothesis builds on the works of Lucas (1972, 1976); Sargent (1971); Sargent and Wallace (1973). The shift from naive to more sophisticated agents sparked a revolution in economic modeling, offering considerable advantages, particularly for conducting policy experiments in stable environments, where the underlying data-generating processes or model structures remain unchanged. However, RE agents lack adaptability in dynamic environments, where structural changes occur. Therefore, the exploration of modeling adaptive agents and understanding their behaviors during such changes remains an important and contentious issue.

Economic agents, or in reality, human beings, exhibit a level of intelligence that falls between that of RE agents and naive adaptive expectations agents. Their expectations and behaviors are intricately nuanced. They engage in exploration of different options, evaluate their actions, draw connections between the present and the past, consider long-term satisfaction, and may also prioritize immediate gratification. When faced with changes in their environment, they demonstrate the ability to adapt (Bassett and Mattar, 2017).

Artificial intelligence (AI) technologies, particularly deep reinforcement learning (RL), have proven effective in enabling artificial agents to learn specific tasks. Core ideas in RL are inspired by phenomena in animal learning, psychology and neuroscience (Subramanian et al., 2022).[1] The RL framework dates back to the 1950s and 1960s, when it combined trial-and-error learning with the formalized Bellman equation. In recent years, it has gained traction through successful applications in fields such as chemistry, robotics, and natural language processing. Notable examples include the development of large language models like ChatGPT and ClaudeAI, as well as breakthroughs in protein structure prediction, for which the researchers behind the AI application were awarded the 2024 Nobel Prize in Chemistry.

Given the limited use of AI technologies as a framework for modeling adaptive economic agents and the complexity inherent in AI frameworks, my objective is to evaluate the ability of an AI agent to adapt and modify its behavior in response to significant environmental changes within a simple dynamic stochastic general equilibrium model. Applying the AI framework aims to provide a complement to the naive form of adaptive expectations and RE while addressing the constraint

[1] For example, Schultz et al. (1997) find that the core of temporal-difference (TD) method can be directly related to actual biological phenomena. Specifically, changes in dopamine levels in the brain—transmitted from certain regions to various target areas—correspond to TD reward prediction errors. The TD method will be introduced in Section 4.

of the RE hypothesis in adapting to structural changes. This change is marked by a shift in the nominal money supply, resulting in the aggregate price sequence transitioning from a stationary state to a non-stationary one. I focus on how well the AI agent adjusts its beliefs and decisions and examine the impact of varying levels of exploration on its adaptive behavior during such an economic shift. These investigations are crucial for demonstrating the practical applicability of AI algorithms in modeling agents with bounded rationality in economies undergoing structural transformations.

I propose to model the adaptive behaviors of an economic agent during a structural change using AI technology, specifically a deep RL framework, for two reasons:

1. AI agents are designed to adapt to structural changes, such as an acceleration in the money supply process, due to their exploration capabilities. This contrasts with RE agents, who excel at a single task and operate based on fixed beliefs, whereas AI agents are designed to be adaptive across various tasks with evolving beliefs.[2]

2. AI agents learn from experience, providing a theoretical framework for modeling experience-based learning.[3] Notably, Malmendier and Nagel (2016) highlight the role of experience in shaping inflation expectations, effectively capturing behaviors observed in microdata.

To conduct the experiment on regime change, I employ a simple dynamic stochastic general equilibrium model that incorporates transaction costs of money demand and utilize a representative AI agent operating according to the deep RL framework. Drawing inspiration from the accelerationist debate, I design the monetary authority to increase the daily growth rate of the nominal money supply from 0% to 1%. The representative AI agent makes two key decisions in each period: the storage decision, determining the quantity of real resources to store (and consume), and the liquidity holding decision, which influences the desired level of real balances to minimize transaction costs. Within the deep RL framework, the agent's policy and value functions are approximated using artificial neural networks (ANNs), allowing flexible adjustment of their forms and parameters.

Through simulation experiments, I find that:

1. The AI agent's capability to adapt its beliefs in response to economic changes is evident in its adjustments to consumption, storage, and demand for real balances. The level of exploration significantly affects this adaptability, which in turn impacts aggregate economic transitions, as shown by the inflation levels following an increase in the nominal money supply. Specifically, after the structural change, inflation rises to 1% in the high-exploration economy, while in the low-exploration economy, it stabilizes around 1.5%.

[2] Along with an extensive review of the literature on the applications of the deep RL framework in economics, Shi (2023) show that this framework involves training AI agents to interact with the economy and take exploratory actions, enabling them to learn from these interactions and adjust their policy and value functions over time.

[3] Hertwig and Erev (2009) discuss the significance of experience in the decision-making process from the perspective of cognitive sciences.

2. As aggregate inflation increases, the total real resources available for AI agents to allocate across decisions—consumption, storage, and liquidity holdings—decrease. Since both agents maintain similar consumption levels in both regimes, they need to reduce their storage and liquidity holdings in the new regime, where fewer real resources are available. The high-exploration agent reduces its liquidity holdings by 25%, more than the low-exploration agent's 22%. As a result, to maintain its consumption level, the low-exploration agent must also reduce its storage, leading to a decrease in wealth. In the new regime, the low-exploration agent accumulates 0.6% less wealth than the high-exploration agent.

3. Due to their exploration feature, the AI agents' beliefs adjust toward those of the RE agent in both regimes but do not fully align. For example, in the new regime, their liquidity holdings decrease compared to the initial regime, similar to the RE agent, but not by the same amount. However, unlike the RE agent, they demonstrate the ability to adjust and adapt to a regime change.

This research provides theoretical insights for policymakers and offering an initial step toward modeling complex adaptive behaviors as a complement to traditional RE models. The findings highlight the importance of incorporating agents' adaptive behaviors and exploration-driven learning into macroeconomic models for economies undergoing structural changes. Different adaptive behaviors can lead to varying transitional dynamics and welfare disparities during such changes.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the economic environment. Section 4 introduces the AI framework and explains its integration with the economic model. Section 5 outlines the parameters used. Section 6 presents the experiments and results. Finally, the paper concludes in the last section.

2 Related Literature

This paper contributes to the literature on modeling agents' expectation formation processes, beginning with the concept of adaptive expectations. Keynes emphasized the importance of agents' expectations when he demonstrated how they influence output and employment (Keynes, 1936). Two decades later, Cagan (1956) and Friedman (1957) formalized the idea of adaptive expectations. Combined with the Phillips curve, their work sparked a significant debate about whether and how a government could exploit the potential negative relationship between inflation and unemployment. However, their approach was criticized for assuming that agents would forecast inflation solely based on the previous period's inflation.

Proposed as an alternative to adaptive expectations was the rational expectations hypothesis, which assumes that agents form model-consistent beliefs and have an understanding of the economy (Lucas, 1976; Sargent, 1971; Sargent and Wallace, 1973). One of its key advantages is its usefulness in analyzing policy experiments in a stationary environment. However, it also has drawbacks, including its inability to provide convincing inflation dynamics in response to shocks. Various techniques have been proposed to strike a middle ground between rational expectations, where agents are too smart, and adaptive expectations, where agents are too naive.

Due to the limitations of the RE framework, an alternative approach proposed was information rigidities, which includes sticky information (Mankiw and Reis, 2002; Ball et al., 2005), noisy information (Woodford, 2001) and rational inattention (Sims, 2003). The main idea is that agents are constrained in obtaining or processing information, and therefore use only a portion of the available information to make 'optimal' decisions. In other words, they still hold model-consistent beliefs but with less than full information.

Another approach proposed focuses on bounded rationality (Sargent, 1993) and adaptive learning (Evans and Honkapohja, 1999). Schorfheide (2005), Ozden and Wouters (2021), and Airaudo and Hajdini (2021) examine the combination of adaptive learning with Markov switching specifications to model learning agents in the context of policy regime changes. In the adaptive learning literature, agents are considered as knowledgeable as econometricians, learning about model parameters by running regressions on past data or using Bayesian updating.

AI agents in this paper share both similarities and differences with the two alternatives proposed as complements to the RE hypothesis. I argue that agents are limited in the amount of information they can collect and process at any given time. However, unlike traditional models, the agents in my approach do not form model-consistent beliefs; instead, they develop decision-making strategies based on their own experiences. Modeling decision-making processes using AI algorithms is also a form of adaptive learning, as it relies on learning from past experience. However, AI agents differ in that they learn from their own interactions with the environment by making exploratory actions.

This paper is similar to recent literature that uses ANNs to model economies. Ashwin et al. (2021) study the stability properties of multiple equilibria with learning agents, where the agents learn using ANNs. Similarly, Kuriksha (2021) models economic agents with deep ANNs in a macro-financial environment. My approach differs in that my learning agents generate their own experiences by interacting with the environment, whereas both Ashwin et al. (2021) and Kuriksha (2021) primarily use deep learning methods (deep ANNs).

This paper is closely related to the emerging literature on the application of deep RL algorithms in macroeconomic models. In Shi (2021), I use a stochastic optimal growth model, and show that an AI agent can learn without prior information about the economic structure or its own preferences, and can adapt to both transitory and permanent income shocks. Recent studies increasingly explore deep RL algorithms as solution methods. Chen et al. (2021) implement a deep RL algorithm in a model with different monetary and fiscal policy regimes, showing that a deep RL agent can locally converge to all equilibria. Hinterlang and Tänzer (2021) employ a deep RL algorithm to solve for optimal policy responses. Additionally, Hill et al. (2021) and Curry et al. (2022) investigate the use of deep RL algorithms in solving multi-agent macroeconomic models.

3 The Model: an Economist's Approach

I employ a transaction cost of money demand model to illustrate the role of money in the economy, akin to Sims (1994). In this model, the preference of individuals for holding money stems from its capacity to diminish transaction costs. Although there are alternative methods to incorporate money into economic models, such as direct integration into utility functions, I opt for the transaction cost approach due to its intuitive appeal. It is important to recognise that money itself does not inherently provide utility; rather, its value derives from its ability to facilitate the purchase of goods and services and its convenience in enabling transactions. In this model, an AI agent is required to determine a policy within a framework that encompasses decisions on both storage and real balance in each period. This represents a departure from Shi (2021), where the agent's decisions were confined to savings each period.

By integrating money into the model, the monetary authority acquires policy leverage to influence the decisions of private agents through changing the growth rate of the nominal money supply. Consequently, this model offers a platform to conduct experiments to explore the behavioral shifts of AI agents in response to a regime change in monetary policy, contrasting with Shi (2021), which focused solely on the real sector of the economy.

I first illustrate how the model is conventionally presented in economics as a benchmark.

3.1 A Representative Household

A representative household aims to maximise its lifetime utility, as outlined in Equation 3.1.

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_t), \tag{3.1}$$

subject to the constraint,

$$c_t(1 + \frac{1}{\kappa} f(v_t)) + s_{t+1} + \frac{M_{t+1} - M_t}{P_t} \leq y_t + s_t^{\alpha} + \tau_t \tag{3.2}$$

where $\beta \in (0,1)$, P_t is the price level at period t, c_t denotes the consumption at t, M_t is nominal money balance, s_t is the saved stock of goods that a household enters period t with, and there is a storage technology that takes the Cobb-Douglas form. y_t is the endowment or income of the agent. τ_t is the government transfer at t.

$\frac{1}{\kappa} f(v)$ represents transactions costs per unit of consumption. $f(v_t) = v_t$, and velocity is $v_t \equiv \frac{c_t P_t}{M_{t+1}}$. Real balance is defined as $m_{t+1} = \frac{M_{t+1}}{P_t}$. Demanding or holding real balance reduces transaction cost.

The endowment depends on a constant $\bar{y}$ and an exogenous process ϵ_t^y, where ϵ_t^y is drawn randomly from a normal distribution with zero mean and variance of 0.01.

$$y_t = \bar{y} + \epsilon_t^y \tag{3.3}$$

3.2 Government: Fiscal and Monetary Policies

The government conducts an active monetary policy and a passive fiscal policy. The monetary authority follows a money growth rule:

$$M_{t+1} = \delta^M M_t, \tag{3.4}$$

where δ^M is a policy variable that determines the speed of money supply. In real terms, this money supply rule becomes,

$$m_{t+1} = \delta^M \frac{m_t}{\pi_t}, \tag{3.5}$$

where real balance $m_t \equiv \frac{M_t}{P_{t-1}}$.

Government budget constraint is,

$$g + \tau_t = \frac{M_{t+1} - M_t}{P_t}. \tag{3.6}$$

The government sets initial nominal money supply and a policy variable δ^M. It also determines a constant government spending g.

Combine the household and the government budget constraints equation 3.2 and 3.6, the consolidated budget constraint is

$$c_t(1 + \frac{1}{\kappa}v_t) + s_{t+1} = y_t + s_t^{\alpha} - g. \tag{3.7}$$

3.3 Household's First Order Conditions (FOCs)

The household's Lagrangian is specified as

$$\mathcal{L} = E_t \sum_{t=0}^{\infty} \beta^t \left\{ ln(c_t) + \lambda_t \left[y_t + s_t^{\alpha} + \tau_t - c_t(1 + \frac{1}{\kappa}v_t) - s_{t+1} - \frac{M_{t+1} - M_t}{P_t} \right] \right\} \tag{3.8}$$

where $v_t = \frac{c_t P_t}{M_{t+1}}$.

The FOC with respect to consumption c_t is ,

$$\frac{1}{c_t} = \lambda_t(1 + \frac{2v_t}{\kappa}). \tag{3.9}$$

The FOC with respect to M_{t+1} is,

$$\frac{\lambda_t}{P_t}(1-\frac{v_t^2}{\kappa}) = \beta E_t \frac{\lambda_{t+1}}{P_{t+1}}. \tag{3.10}$$

The FOC with respect to s_{t+1} is,

$$\lambda_t = \alpha\beta s_{t+1}^{\alpha-1} E_t \lambda_{t+1}. \tag{3.11}$$

3.4 Non-Stochastic Steady States and Determinancy

The equations governing the dynamic system of this model consist of the first-order conditions, specifically Equations 3.9, 3.10, and 3.11, alongside the consolidated budget constraint, the rule governing the money supply, and the process determining the endowment. Additionally, I incorporate the definition of velocity directly into these equations and use inflation instead of price levels. Inflation is defined as $\pi_t = \frac{P_t}{P_{t-1}}$.

$$\begin{aligned}
\left[\frac{1/c_t}{1+\frac{2c_t}{\kappa m_{t+1}}}\right]\left[1-\frac{c_t^2}{\kappa m_{t+1}^2}\right] &= \beta E_t \frac{\frac{1/c_{t+1}}{1+\frac{2c_{t+1}}{\kappa m_{t+2}}}}{\pi_{t+1}} && (3.12)\\
\left[\frac{1/c_t}{1+\frac{2c_t}{\kappa m_{t+1}}}\right] &= \alpha\beta s_{t+1}^{\alpha-1} E_t \left[\frac{1/c_{t+1}}{1+\frac{2c_{t+1}}{\kappa m_{t+2}}}\right] && (3.13)\\
m_{t+1} &= \delta^M \frac{m_t}{\pi_t} && (3.14)\\
c_t(1+\frac{c_t}{\kappa m_{t+1}}) + s_{t+1} &= y_t + s_t^{\alpha} - g && (3.15)\\
y_t &= \bar{y} + \epsilon_t^y && (3.16)
\end{aligned}$$

To solve for the non-stochastic steady state, I assume zero shock and constant real variables. The non-stochastic steady state values are presented in Table 5, given the specified parameters.

I arrange the equations in the form of Equation 3.17.

$$E_t f\{Y_{t+1}, Y_t, X_{t+1}, X_t\} = 0 \tag{3.17}$$

where E_t denotes the expectations operator conditional on information available at time t. The state vector is $X_t = [s_t, y_t, m_t]'$. The co-state vector is $Y_t = [c_t, \pi_t]'$.

The steady state is locally determinate and unique. I check whether the non-stochastic steady state is locally determinant by deriving the Jacobians of this system, as written in the form of Equation 3.17. I calculate generalized eigenvalues using QZ decomposition, all in accordance with the parameters stated in Section 5. I calculate the list of eigenvalues to be $[0, 1, 0.18, 5.48, 0]$. There are three stable roots, two unstable ones, and two co-states are solved from three state variables.

Therefore, I conclude that the steady state is unique and locally determinate. The same exercise is repeated for the second regime with an increasing supply of nominal balance, leading to the same conclusion: the steady state is locally determinate and unique.

4 The Model: an AI Approach

I begin this section by introducing the AI learning framework, outlining its key components and highlighting the importance of the exploration feature. This is followed by the implementation details for the specific model presented in Section 3, along with a full description of the algorithm.

4.1 An AI Learning Framework: a Brief Introduction

RL is a type of AI technology where agents learn by interacting with an environment, taking actions, and receiving rewards based on their actions. Deep RL extends this concept by using deep neural networks to approximate value or policy functions, which guide the agent's decision-making process. In RL, the learning process relies on the agent generating data by interacting with the environment, using these experiences to improve its performance and solve complex problems. Sutton and Barto (1981) provide a comprehensive review of RL algorithms.

Unlike supervised learning, which requires labeled training data to evaluate its predictions, or unsupervised learning, which seeks to find patterns in unlabeled data, RL does not need a predefined training dataset. Instead, it learns through continuous interaction with its environment. The agent receives feedback via a reward function, which informs it whether its actions are beneficial or not, helping it optimize its behavior over time.

RL originated from early studies in psychology and neuroscience, where it was initially developed to explain how animals learn through experience. As detailed in Tohid and Shi (2022), pioneers such as Alan Turing, Norbert Wiener, and Richard Bellman initially explored these ideas, which later gained significant traction in computer science during the 1970s. Two key concepts underpinning RL's development were temporal difference (TD) learning, which involves trial-and-error learning, and optimal control, rooted in dynamic programming. RL reached the machine learning community in the late 1980s, leading to breakthroughs such as Watkins' Q-learning algorithm. By the 1990s, RL was applied to real-world problems like backgammon, achieving human-level performance, and began to merge with techniques like neural networks and evolutionary computation. By the late 2000s, the integration of RL with deep learning facilitated applications in complex fields such as robotics, healthcare, and finance, significantly advancing the field.[4]

[4]For example, machines trained with the deep Q-network algorithm (Mnih et al., 2013) achieved human-level performance on many Atari video games using raw pixels as input. However, the deep Q-network algorithm is limited to discrete action spaces. For continuous action spaces, the deep deterministic policy gradient (DDPG) algorithm from Lillicrap et al. (2015) is often employed.

4.2 An AI Learning Framework: the Actor-Critic Model

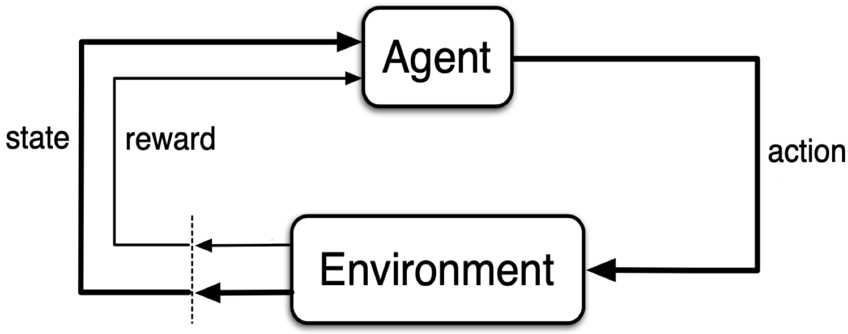
The specific deep RL algorithm adopted here was first introduced by Lillicrap et al. (2015), namely deep deterministic policy gradient (DDPG). [5] This algorithm mainly follows the actor-critic model of reinforcement learning, and it uses the formal framework of a Markov Decision Process (MDP) to define the interactions between a learning agent and its environment in terms of states, actions, and rewards (Figure 1).

State S is a random variable from a state space, which is a bounded and compact set,[6] i.e., $S \in \mathcal{S}$. The agent takes an action A, which belongs to an action space $\mathcal{A}$, $A \in \mathcal{A}$. The state evolves through time following a probability function, $p : \mathcal{S} \times \mathcal{S} \times \mathcal{A} \rightarrow [0, 1]$, which is defined as

$$p(S'|S, A) \equiv Pr\{S_t = S'|S_{t-1} = S, A_{t-1} = A\}. \tag{4.18}$$

It shows the probability of a random variable state S' occurring at time t, given the preceding values of state, S, and action, A.

Figure 1: The agent-environment interaction in a reinforcement learning setting



Source: Sutton and Barto (2018)

Reward is a random variable and can be generated from a reward function, $R : \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{R}$.

The return from a state is defined as the sum of discounted future rewards,

$$G_t \equiv R_t + R_{t+1} + ... = \sum_{k=0}^{\infty} \beta^k R_{t+k}, \tag{4.19}$$

where β is the discount factor.

[5] Chen et al. (2021) also adopt the DDPG algorithm in their study of learnability of rational expectations equilibrium in different policy regimes.

[6] The latest research on reinforcement learning also investigates the setting with unbounded state space, e.g., Shah et al. (2020).

A RL learning agent's behaviors follow a policy function, also known as the actor network. The policy function can be both stochastic and deterministic. A stochastic policy maps states to probabilities of selecting each possible action. A deterministic policy, which is used in this paper, maps a state from a state space to an action from an action space, and it is denoted by $\mu : \mathcal{S} \to \mathcal{A}$.

A value function[7], also known as the critic network, shows the 'expected' returns of taking an action in a state and thereafter following policy μ. Expectations here are subjective beliefs that depend on learning agents' past experiences. A value function is defined as,

$$Q^{\mu}(S, A) \equiv E^{\mu}[G_t | S_t = S, A_t = A], \tag{4.20}$$

where Q^{μ} means the action value function follows policy μ, and E^{μ} reflects that it's a subjective belief that depends on a policy μ that is formed by past experience.[8]

Many approaches in reinforcement learning make use of the recursive relationship known as the Bellman equation,

$$Q^{\mu}(S, A) = R(S, A) + \beta E^{\mu} Q(S', A'), \tag{4.21}$$

where $A' = \mu(S')$.

RL methods focus on how the learning agents' policy and value functions change as a result of their experience. These changes can be a functional form change or parameter value updates. The DDPG algorithm uses ANNs to approximate policy and value functions: the actor network is denoted as $\mu(S|\theta^{\mu})$, where θ^{μ} represents parameters of the ANNs; the critic network is denoted as $Q(S, A|\theta^{Q})$, and θ^{Q} is its parameters. θ^{μ} and θ^{Q} are updated during learning, and can be viewed as the coefficients of two functions and the probabilities involved in making subjective expectations. Two ANNs are updated with respect to each other.

The goal of RL learning agents is to continuously update their subjective beliefs about the world based on experience, and to form a decision-making strategy (approximated by the actor network) that produces the highest discounted future returns (approximated by the critic network). The actor network is updated with the goal of maximizing the corresponding critic network. In other words, the actor network is updated based on what the agent believes, at that time, to be a strategy that produces high 'expected' returns. The critic networks evolves over time. What the agent follows as the critic network at period t is different from what it is at $t + 1$. Expectations are the learning agents' subjective beliefs that are formed from past experience.

The critic network is updated with the goal of minimising a TD error (a temporal difference error).[9] The TD error follows the form,

[7] In reinforcement learning literature, two types of value functions are defined: action-value function and value function. To not complicate the matter, I use value function as action-value function throughout this paper.

[8] This forms of notation, e.g., E^{μ}, largely follows The Handbook for Reinforcement Learning by Sutton and Barto (2018).

[9] The full algorithm is in the next section.

$$T - Q(S, A|\theta^Q), \tag{4.22}$$

where T is called a TD target, and it adds the reward given a state-action pair to the discounted values of the next state and action, i.e.,

$$T = R(S, A) + \beta Q(S', A'|\theta^Q) \tag{4.23}$$

and the next period action A' is assumed to follow the actor network $\mu(S|\theta^\mu)$ at that time.[10]

$$A' = \mu(S'|\theta^\mu). \tag{4.24}$$

Intuitively, TD targets represent the best possible returns learning agents receive following a state-action pair and their subjective beliefs.

Neural science research shows that the dopamine neuron firing rates in the brain resemble the TD error sequence during learning (Botvinick et al., 2019). This motivates research in neural science to model decision-making in connection with RL algorithms.

4.3 An AI Learning Framework: Exploration

Explorations play a crucial role because learning agents that make exploratory actions collect a wide range of information. An exploratory policy is defined as,

$$\mu'(S_t) = \mu(S_t|\theta^\mu) + \mathcal{N}_t. \tag{4.25}$$

This shows that the final action the agent takes, i.e., what $\mu'(S_t)$ generates, depends on the actor network $\mu(S_t|\theta^\mu)$, and a random variable sampled from a noise process $\mathcal{N}_t$. Following Lillicrap et al. (2015), $\mathcal{N}_t$ is sampled from a discretised Ornstein-Uhlenbeck (OU) process.[11]

This exploratory policy produces random actions. The randomness decreases over time (by design) but it never disappears. The implication is that in a stationary environment, the agents learn their policy functions, and the learnt functions can be similar to the true policy function but may never be identical. However, in a non-stationary environment, explorations allow the policy network to adjust and be flexible to changes in the environment.

The exploration strategy implies that the policy function can converge to a close region of the rational expectation solution (if it exists), but will not be identical to it. In an environment with structural breaks or regime changes, this exploratory policy allows the learning agent to adjust its expectations and adapt its policy to a new regime. While my focus is on the exploration-driven

[10] It need not be the same as the true policy.

[11] There is a strain of literature in computer science that solely focuses on different exploration strategies to achieve the best performance for a given task. It is out of the scope of the current exercise, and not discussed here.

adaptive learning framework provided by the DDPG algorithm, many RL algorithms aim to address dynamic programming problems with reduced computational effort and without relying on a perfect model of the environment (Sutton and Barto, 2018).

4.4 Bridge AI and Economics

To apply and implement the AI framework, the economic model is first translated into components of a MDP, including state, action, reward, and next state[12]. These components are summarized in Table 1. The state variables encompass current period income and storage technology. The agent is also aware of past period inflation, real balance, and storage level.

The actions available to the AI agent consist of determining the proportion of real resources to store, λ_t^s, and the desired level of real balance to demand, m_{t+1}. Based on its storage decision, the agent allocates resources for consumption. Likewise, its decision on real balance demand affects transaction costs and aggregate inflation dynamics. In this representative agent model, the AI agent's demand for real balance represents the aggregate money demand, although in multi-AI agent studies, aggregate money demand would differ from individual demands for real balance.

Table 1: RL Components and the Economic Environment

Terminologies	**Description**	**Representation in the economic environment**
State, S_t	A random variable from a state space, $S_t \in \mathcal{S}$	$S_t = \{y_t, \pi_{t-1}, m_t, s_t\}$
Actions, A_t	A random variable from an action space, $A_t \in \mathcal{A}$	$A_t = \{\lambda_t^s, m_{t+1}\}$
Rewards, R_t	A function of state and action	$R_t = ln(c_t)$
Policy function, $\mu(S\|\theta^\mu)$	A mapping from state to action, $\mu : \mathcal{S} \to \mathcal{A}$	Approximated by a neural network, i.e., actor network; parameterised by θ^μ to be updated during learning
Value function, $Q(S, A\|\theta^Q)$	The 'expected' (subjective belief) return from taking an action in a state	Approximated by a neural network, i.e., critic network; parameterised by θ^Q to be updated during learning

[12]To avoid confusion with the storage variable s_t, I use capital letters to denote deep RL-related terms: state (S_t), action (A_t), and reward (R_t).

The reward function, $R_t = ln(c_t)$, is influenced by the agent's level of consumption, c_t. Higher consumption leads to greater rewards per period. Policy ($\mu(S|\theta^{\mu})$) and value ($Q(S, A|\theta^Q)$) functions are approximated using two deep neural networks. The AI agent aims to develop a decision-making strategy that maximizes its performance not only in each period but also over the long run, as measured by cumulative rewards. The agent seeks consistent high-level rewards rather than focusing solely on maximizing rewards in a single period.

Consequently, the agent faces two critical decisions: 1) determining the balance between storage and consumption, and 2) managing transaction costs through the allocation of resources to hold money. Higher storage allows for increased future consumption when adverse income or endowment shocks occur, though it means consuming less in the current period. The second decision involves optimizing the allocation between money and real goods. Holding more money reduces transaction costs but limits the real goods available for consumption or storage. Conversely, holding less money frees up more real goods for consumption or storage but increases transaction costs.

4.5 Full Algorithm and Sequence of Events

The complete algorithm comprises three main steps: initialization, interaction, and learning.

Step I. Initialization

- In a given environment, design a state space $\mathcal{S}$, a continuous bounded and compact set for random variables specified in Table 1; design an action space $\mathcal{A}$, a continuous bounded and compact set for the action (random) variables.
- Set up two deep ANNs: an actor network $\mu(S|\theta^{\mu})$ takes the argument of a state from the state space and generates an action within the action space; a critic network $Q(S, A|\theta^Q)$ takes the argument of a realised state-action pair and generates a value. Setting up two ANNs involves determining the input and output dimensions, the specific architectures, the number of layers, the number of nodes per layer, and how nodes are connected.
- θ^{μ} represents the parameters of the actor network, and θ^Q represents the parameters of the critic network.
- Define a memory $\mathcal{B}$ (called replay buffer or transitions in the deep RL literature), which stores information that is collected by a deep AI agent during the agent-environment interactive process. One period memory (or a transition) is characterised by a sequence of variables (S_t, A_t, R_t, S_{t+1}).
- Define a length of N, which is the size of a mini-batch. A mini-batch refers to a sample drawn from the memory, $\mathcal{B}$.

- Define the total number of episodes E and simulation periods per episode. The higher the episodes, the longer the learning periods.[13]

- Lastly, a simulation period of T is established for each episode, with T exceeding the value of N.

For each episode, define the initial state,[14] and loop Steps II and III.

Step II. Interaction: the AI agent starts to interact with its environment for $t \leq T$. This step involves how agents' actions are chosen and how their actions impact the aggregate economy.

- Assume $\delta^M = 1.00$ (δ^M=1.01 in the new regime) and other variables that are known to the agent at period t: y_t, π_{t-1}, m_t, s_t.

- The agent selects a random (based on the randomly initialised actor network) of action variables, $A_t = \mu(S_t|\theta^\mu) + \mathcal{N}_t$, and A_t contains λ_t^s and m_{t+1}, and $\mathcal{N}_t$ is a noise attached to the action to ensure exploration, which is sampled from an AR(1) process.

- Given the exogenous (to the AI agent) nominal money supply from the government, $M_{t+1} = \delta^M M_t$, with aggregate money demand equal to aggregate money supply, price level or inflation can be derived as $\pi_t = \frac{M_{t+1}}{M_t}\frac{m_t}{m_{t+1}} = \delta^M \frac{m_t}{m_{t+1}}$. In a one-agent case, aggregate money demand at period t is m_{t+1}.

- The amount stored is $s_{t+1} = \lambda_t^s(y_t + \frac{m_t}{\pi_t} + s_t^\alpha + \tau_t - m_{t+1})$.

- c_t is reached from the budget constraint.

- The new state variables are $S_{t+1} = \{y_{t+1}, \pi_t, m_{t+1}, s_{t+1}\}$, where $y_{t+1} = \bar{y} + \epsilon_{t+1}^y$, and ϵ_{t+1}^y is sampled from a normal distribution $N(0, 0.01)$, $\bar{y} = 1$.

- The reward the agent receives is, $R_t = u(c_t)$.

- Store a transition (S_t, A_t, R_t, S_{t+1}) in the memory $\mathcal{B}$.

Step III. Learning: training the AI agent (when the AI agent starts to learn) for period $N \leq t \leq T$.

- Sample a random mini-batch of N transitions (S_i, A_i, R_i, S_{i+1}) from the memory $\mathcal{B}$.

- Calculate the TD-target values TD_i for each transition $i \in N$ following

$$TD_i = R_i + \beta Q^\mu(S_{i+1}, \mu(S_{i+1}|\theta^\mu)|\theta^Q) \tag{4.26}$$

  where $Q^\mu(S_{i+1}, \mu(S_{i+1}|\theta^\mu)|\theta^Q)$ is a prediction made by the critic network with state-action pair $(S_{i+1}, \mu(S_{i+1}|\theta^\mu))$, and $\mu(S_{i+1}|\theta^\mu)$ is a prediction made by the actor network with input S_{i+1}.

[13]In the deep RL literature, the AI agent is usually set to learn a particular task or an Atari game. An episode thus means re-starting the game or task, and it ends with a terminal state (i.e., the end result of a game). In an economic environment, however, a clear terminal state can be difficult to specify. Therefore, the concept of episodes only correlates to how long an agent has been learning.

[14]Initial state variables can also be randomly drawn from the state space.

- Obtain $Q(S_i, A_i|\theta^Q)$ from the critic network with input state-action pair (S_i, A_i)
- Calculate the average loss for this sample of N transitions

$$L = \frac{1}{N}\sum_i \left(TD_i - Q(S_i, A_i|\theta^Q)\right)^2 \tag{4.27}$$

- Update the critic network with the objective of minimising the loss function L.[15]
- For the policy function, i.e., the actor network, the objective is to maximise the value function predictions. Define the objective function as,

$$J(\theta^\mu) = Q^\mu(S_i, \mu(S_i|\theta^\mu)|\theta^Q). \tag{4.28}$$

- Maximising this objective function is equivalent to minimising $-J(\theta^\mu)$. Update the actor network parameters θ^μ with the objective of minimising $-J(\theta^\mu)$.[16]

5 Parameters and (Non-Stochastic) Steady State Values

I choose the discount factor to be 0.99999 so that each simulation period corresponds to a day. The rest of the parameters are uncalibrated. Under the baseline regime, the annual growth rate of the nominal money supply is assumed to be zero, and government spending is also set to zero. The parameter for the transaction cost function was chosen to be 1000. In the scenario of a monetary regime change, there is a shift in the daily growth rate of the nominal money supply from 0 to 1%. This shift does not represent a realistic change in real-world regimes. The purpose of this drastic shift is to facilitate comparison of steady-state values across the two regimes, enabling an AI agent to detect differences.[17]

[15] This involves applying backpropagation and gradient descent procedures.

[16] Similar to the critic network, the specific steps of updating ANN's parameters by minimising an objective function involve backpropagation and gradient descent.

[17] When the two steady states have similar reward values, the AI agent struggles to detect changes effectively. This finding highlights the need for further research and experimentation to better understand how the size or extent of differences in reward values affects the agent's ability to recognize and adapt to these changes.

Table 2: Baseline Parameters and Steady State Values

	Regime I	**Regime II**
Storage technology parameter, α	0.4	
Discount factor, β	0.99999	
Endowment, $\bar{y}$	1	
Government spending, g	0	
Transaction cost function parameter, κ	1000	
Exploration	Low - 0.008; High - 0.02	
Monetary policy parameter, δ^M	1.0	1.01
RE velocity, v	0.1	3.148
Consumption, c	1.326	1.322
Storage, s	0.217	0.217
Real balance, m	13.256	0.420

6 Experiments and Results

6.1 Experiments

In this exercise, I study the adaptive behaviors of a representative AI agent when the environment undergoes a drastic change. I investigate the role of exploration in facilitating the adaptive behaviors of AI agents, and how different levels of exploration may shape the beliefs and behaviors of these agents. Following the full algorithm outlined in Section 4.4, I conduct the following experiment.

A representative AI agent is introduced into an economy with a constant nominal money supply, which then undergoes an increase in the nominal money supply. The change in nominal money supply is unknown to the AI agent. The AI agent operates under the initial policy regime for approximately 27 years. Then, without prior announcement, there is a shift to a new regime where the nominal money supply increases daily at a rate of 1%.[18] The AI agents live in the new regime

[18] This shift does not represent a realistic change in real-world regimes. The purpose of this drastic shift is to facilitate comparison of steady-state values across the two regimes, enabling an AI agent to detect differences.

for around 60 years. Designing the regime change as an adjustment to the money supply process is intended to demonstrate the AI agent's ability to adapt to structural changes, and is rooted in the accelerationist debate.

Given its adaptive and explorative nature, the AI agent is expected to adjust to a monetary policy regime change by adapting its consumption and liquidity holding decisions. Through this experiment, I aim to examine the agent's adaptability, the extent of its adjustments in beliefs and decisions, and how the level of exploration affects its adaptive behavior during such a significant economic shift.

To examine the role of exploration, I set up two AI agents, one with a high level of exploration and the other with a low level, to start in the same economy under identical initial conditions. I then subject both agents to the same regime change experiment to observe and compare their responses. Additionally, I compare the simulation paths of the AI agents against those of an RE agent in both regimes. I replicate the simulation experiment 50 times and analyze the median results. These results, representing the median performance across the repetitions, provide a stable basis for comparison.

Moreover, the plots, derived from simulations conducted during the testing period in which agents operate without further updates or exploration, illustrate what the AI agents would have done after experiencing a regime change and living under the new regime for 60 years. This means that the beliefs have already been updated after experiencing a regime change. Therefore, direct changes in behavior or aggregate variables can be observed as a result of regime changes in the simulation paths. These plots aim to facilitate the comparison of different agents' behaviors and their comparison with the path of the RE agent.

Through this experiment, I highlight three main findings:

1. The AI agent's capability to adapt its beliefs in response to economic changes is evident in its adjustments to consumption, storage, and demand for real balances. The level of exploration significantly affects this adaptability, which in turn impacts aggregate economic transitions, as shown by the inflation levels following an increase in the nominal money supply. Specifically, after the structural change, inflation rises to 1% in the high-exploration economy, while in the low-exploration economy, it stabilizes around 1.5%.

2. As aggregate inflation increases, the total real resources available for AI agents to allocate across decisions—consumption, storage, and liquidity holdings—decrease. Since both agents maintain similar consumption levels in both regimes, they need to reduce their storage and liquidity holdings in the new regime, where fewer real resources are available. The high-exploration agent reduces its liquidity holdings by 25%, more than the low-exploration agent's 22%. As a result, to maintain its consumption level, the low-exploration agent must also reduce its storage, leading to a decrease in wealth. In the new regime, the low-exploration agent accumulates 0.6% less wealth than the high-exploration agent.

3. Due to their exploration feature, the AI agents' beliefs adjust toward those of the RE agent in both regimes but do not fully align. For example, in the new regime, their liquidity holdings decrease compared to the initial regime, similar to the RE agent, but not by the

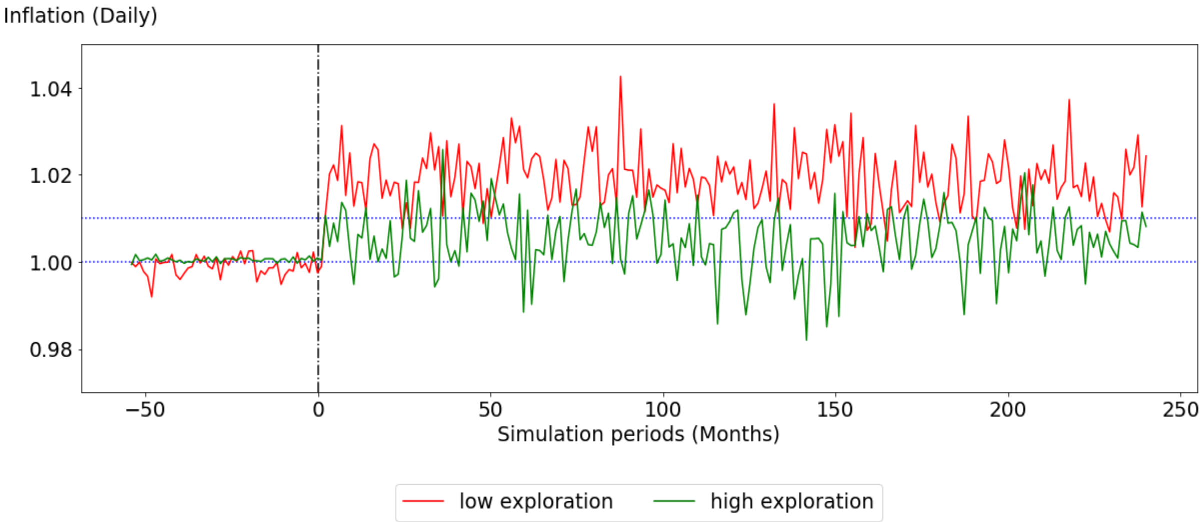
same amount. However, unlike the RE agent, they demonstrate the ability to adjust and adapt to a regime change.

6.2 Inflation

Inflation rises following an increase in the nominal money supply, but the extent of the increase varies depending on the level of exploration exhibited by the representative AI agent. Before the regime change, inflation in both economies was around 0%, but after an adjustment period, it stabilized at around 1% in one economy and 1.5% in the other, depending on the exploration level of the AI agent. In Figure 2, the red line represents the low-exploration economy, and the green line represents the high-exploration economy. Following the regime shift, inflation in the high-exploration economy becomes volatile before stabilizing at 1%, while in the low-exploration economy, it stabilizes around 1.5%.

In a high-inflation environment, the total real resources available decrease, prompting an adaptive AI agent to adjust its allocations across consumption, storage, and liquidity holding. Examining how the AI agents adjust their consumption, storage, and liquidity holding decisions in response to this regime change can provide better insight into their adaptive behaviors. In particular, will the AI agents reduce their consumption, storage, and/or liquidity holdings to adjust to the reduced overall real resources? How would their behaviors differ based on their exploration levels?

Figure 2: Inflation

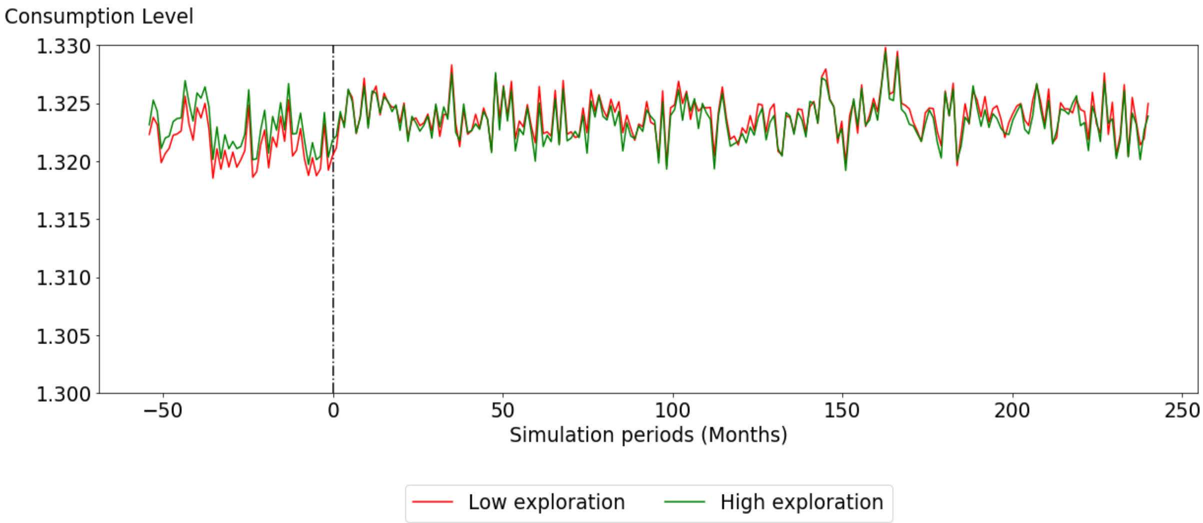


Notes:
1. The x-axis represents simulation periods in months.
2. The y-axis plots daily inflation, where inflation is defined as current period price level divided by the previous period price level.
3. The horizontal dashed lines mark the initial steady state inflation at 0% and the new steady state inflation at 1%, respectively.
4. A vertical dashed line at period 0 represents the occurrence of the regime change.
5. The red line represents the variable of interest for the low-exploration AI agent, and the green line represents that for the high-exploration AI agent.

6.3 Consumption, Storage, Liquidity Holding, and Wealth

Both AI agents exhibit consumption smoothing behavior and reach similar levels of consumption across both regimes, demonstrating their adaptability to structural changes in the economy. Figure 3 illustrates this behavior, beginning 50 months before the regime shift, with period 0 marking the transition. The plots show that consumption remains stable even after the economy shifts to a high-inflation state. This smoothing behavior indicates that both agents achieve similar reward levels before and after the regime change. To sustain their consumption levels despite a reduction in aggregate real resources in a high-inflation environment, the agents must decrease either storage, liquidity holdings, or both.

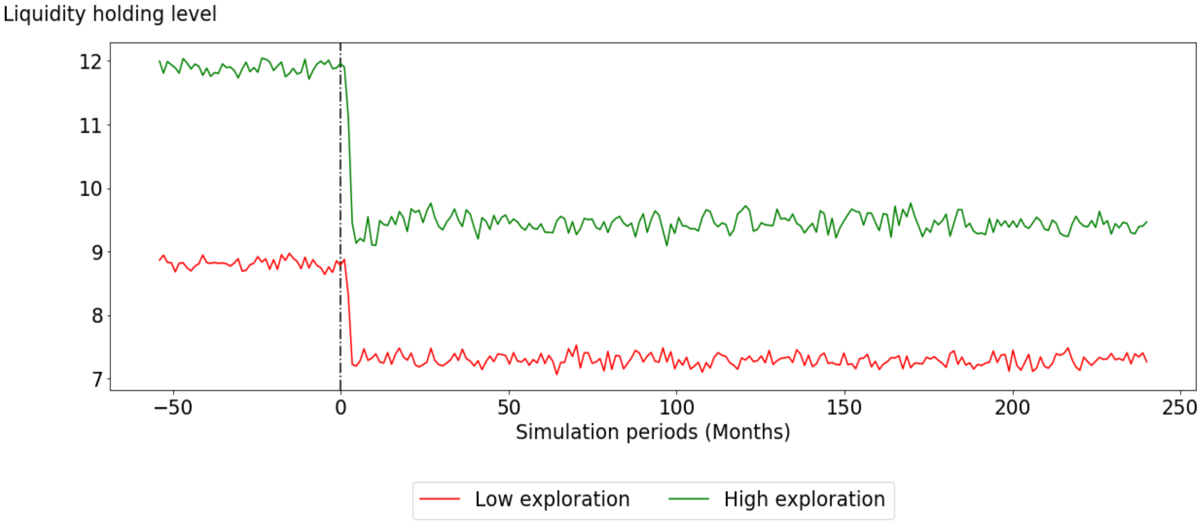
Figure 3: Consumption of AI Agents during a Regime Change



Notes:
1. The x-axis depicts simulation periods in months.
2. The y-axis represents the consumption level.
3. A vertical dashed line at period 0 indicates the occurrence of the regime change. This regime change involves an acceleration of the nominal money supply from a 0% to a 1% daily growth rate.
4. The red line illustrates the variable of interest for the low-exploration AI agent, while the green line represents the same variable for the high-exploration AI agent.

Both agents reduce their liquidity holdings after transitioning from a low- to high-inflation environment to support their desired consumption levels, with the high-exploration agent reducing more than the low-exploration agent. Holding liquidity helps reduce transaction costs when consuming. In a high-inflation regime, real resources are lower than in a low-inflation regime, making it less desirable to allocate the same amount to real balances. Through exploration, AI agents adapt their beliefs and reduce their liquidity holdings to function effectively in the new regime. The high-exploration agent reduces its liquidity holdings by 25% to adjust to the new regime, while the low-exploration agent decreases its liquidity holdings by around 21% following the regime change.

Figure 4: Real balance



Notes:

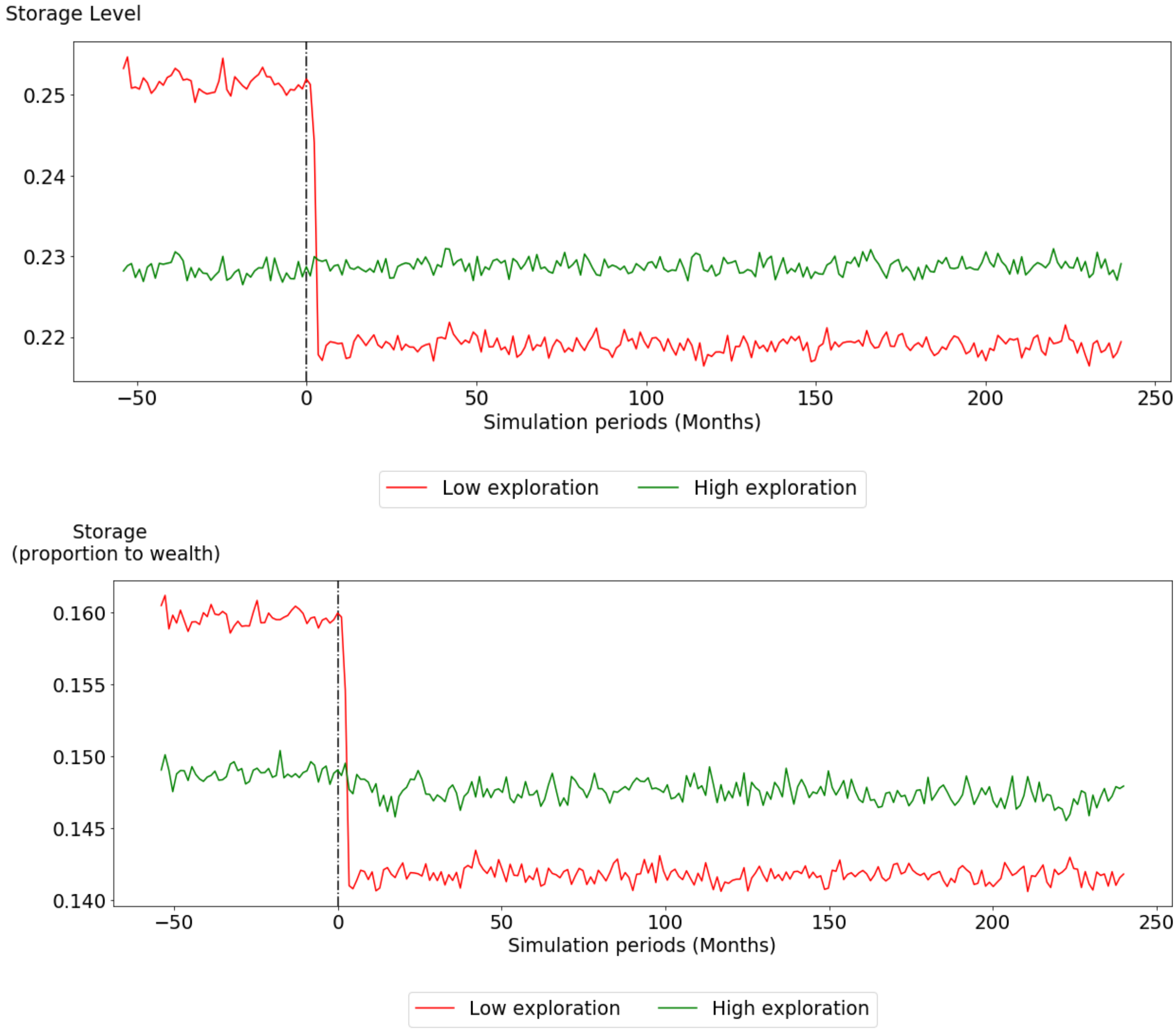
1. The x-axis represents simulation periods in months.
2. The y-axis displays the level of liquidity holding by the AI agents.
3. A vertical dashed line at period 0 signifies the occurrence of the regime change. This regime change involves an acceleration of the nominal money supply from a 0% to a 1% annual growth rate.
4. The red line represents the variable of interest for the low-exploration AI agent, while the green line depicts the same variable for the high-exploration AI agent.

After the regime change, the high-exploration agent sustains its storage and wealth, while the low-exploration agent, reducing liquidity holdings less, must lower its storage to maintain pre-change consumption levels. As shown in Figure 5, the high-exploration agent maintains a storage level of 0.23, while the low-exploration agent maintains a storage level of 0.25. After the regime shift, the low-exploration agent reduces its storage level by 12%, which accounts for around 14% of its wealth, compared to 16% before the regime shift. This reduction in storage contributes to the overall decline in aggregate wealth following the regime change.

The high-exploration agent maintains a consistent storage level, keeping its wealth largely unchanged, while the low-exploration agent's wealth decreases after the regime change, resulting in a 6% difference between the two. Figure 6 shows the wealth levels for AI agents with different exploration levels. Wealth at period t is defined as $y_t + s_t^\alpha$, where lower storage means less wealth for the same income, y_t. Both agents start with the same initial wealth (Figure 6, bottom panel). Although their wealth levels differ in the initial regime due to varying exploration,[19] the low-exploration agent's significant storage reduction during the regime change causes its wealth to drop, leaving the high-exploration agent's wealth around 0.6% higher.

[19]Since the focus of this paper is on the adaptability of AI agents to regime changes, I will not discuss the variations in outcomes during the initial regime due to different levels of exploration. For more information on this, please refer to Shi (2021).

Figure 5: Storage of AI Agents during a Regime Change



Notes:

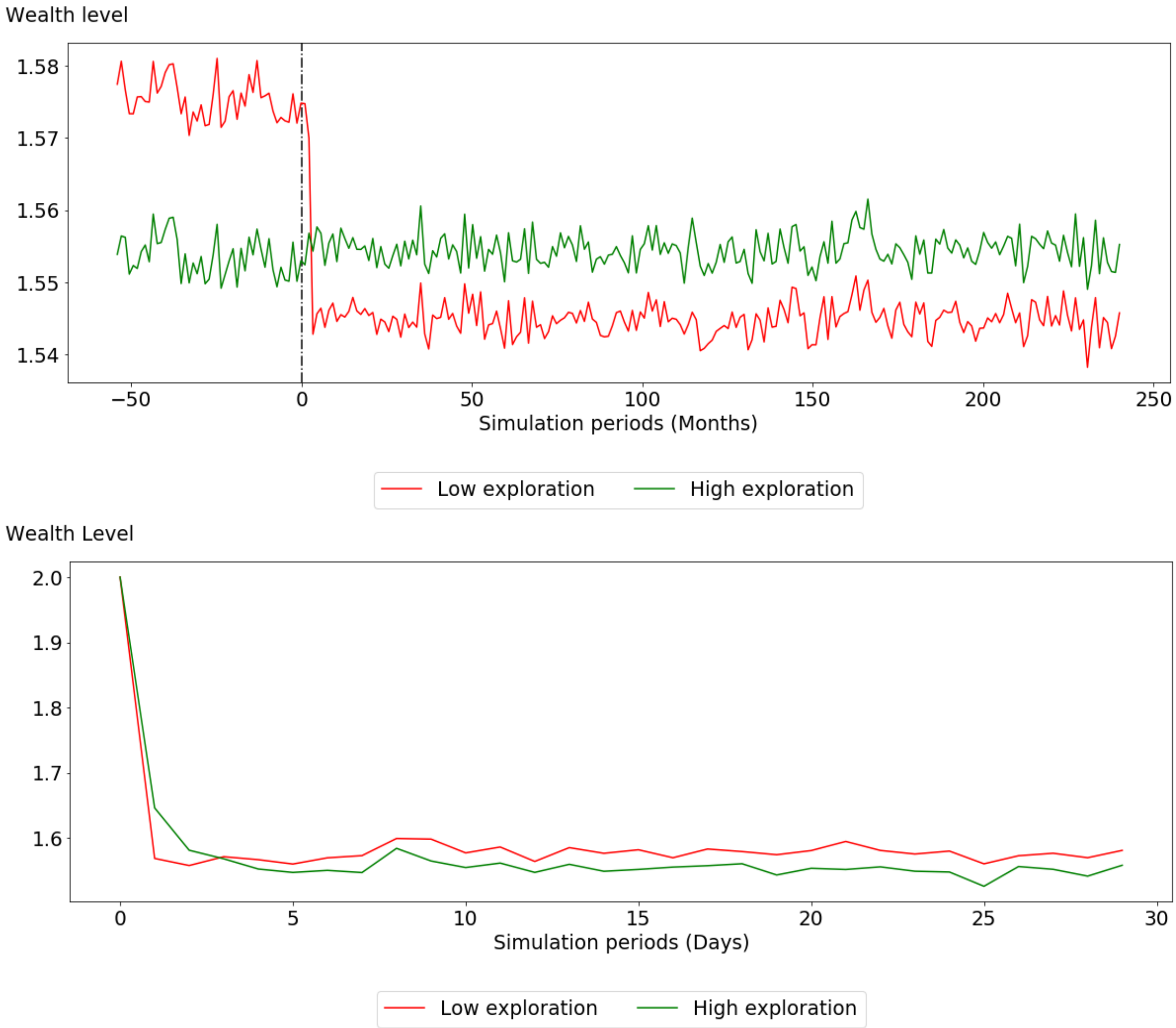
1. The x-axis depicts simulation periods in months.

2. The y-axis represents the savings/storage level in the top panel, and the proportion of savings to wealth in the bottom panel, where wealth at period t is defined as $y_t + s_t^{\alpha}$, encompassing both income and previous storage.

3. A vertical dashed line at period 0 indicates the occurrence of the regime change. This regime change involves an acceleration of the nominal money supply from a 0% to a 1% daily growth rate.

4. The red line illustrates the variable of interest for the low-exploration AI agent, while the green line represents the same variable for the high-exploration AI agent.

Figure 6: Wealth



Notes:

1. The x-axis represents simulation periods in months in the top panel, and days in the bottom panel.

2. The top panel displays the level of wealth in the economy during a regime change, where wealth at period t is defined as $y_t + s_t^{\alpha}$.

3. The initial level of wealth, shown in the bottom panel figure, is identical for both economies, set at an arbitrary value of 2.

4. The red line represents the variable of interest for the low-exploration AI agent, while the green line depicts the same variable for the high-exploration AI agent.

5. A vertical dashed line at period 0 signifies the occurrence of the regime change on the top panel. This regime change involves an acceleration of the nominal money supply from a 0% to a 1% daily growth rate.

6. In the bottom panel, Period 0 represents the initial period of the first regime.

6.4 AI vs RE agent(s)

It's crucial to emphasize that although an RE agent performs well in a stable environment, AI agents adept in adapting to changes within their environment thanks to their exploratory behavior. This adaptability is primarily attributed to the exploration mechanisms inherent in deep RL algorithms, setting them apart from the RE agents. As a result, AI agents are capable of adjusting their behaviors in response to environmental shifts, and their beliefs never fully align with those of an RE agent, sidestepping the limitations posed by the Lucas Critique.

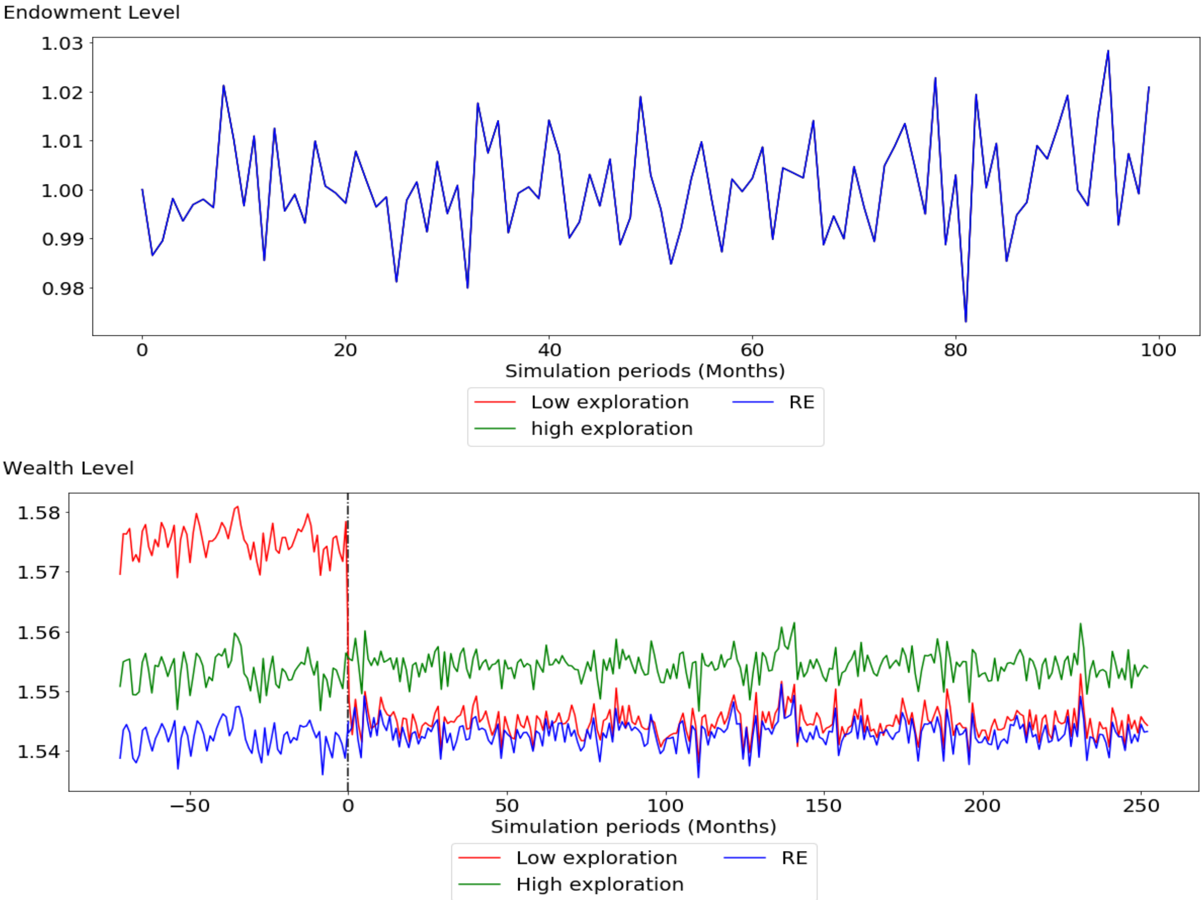
To highlight this distinction, I compare the behavior of an RE agent across the two regimes with AI agents. I solve for the RE equilibrium in each regime separately and then combine the two simulations, labeling this sequence as the RE agent's behavior in Figures 7 and 8.[20] Since the RE agent is constrained by a fixed belief in each regime, this approach avoids the debate over whether the RE agent is aware of the regime change or if it occurs unexpectedly. Additionally, I include the performance of AI agents with both low and high exploration levels, as introduced in the previous section. This comparison highlights the differences between the AI agents and the RE agent. The top panel of Figure 7 depicts the endowment process for both AI and RE agents, illustrating that they operate in an identical environment with the same shock process. As all agents operate under the same conditions, only one line is observable in the figure.

Across both regimes, the consumption levels of all agents are similar but not identical (Figure 8), with AI agents tending to save more than the RE agent. The RE agent reduces its consumption modestly by around 0.3% after the regime shift, while both AI agents seem to consume similar amounts after the change. The high-exploration agent saves about 4% more than the RE agent, while the low-exploration agent saves around 12% more in the initial regime, dropping to just 0.03% more in the new regime. One possible explanation for the higher savings observed in AI agents is that they save extra to allow for more exploration in the future when needed.

Comparing the simulation paths of AI agents with those of the RE agent shows that AI agents adapt their decisions toward the RE agent, though the magnitude of their behavior differs, influenced by their levels of exploration. AI agents' liquidity holdings drop by 22% to 25%, depending on their levels of exploration, while the RE agent's liquidity holdings decrease by around 90%. Additionally, as AI agents save more than the RE agent, they accumulate more wealth. In the new regime, the low-exploration agent accumulates around 0.1% more wealth than the RE agent, while the high-exploration agent accumulates around 0.7% more.

[20]The RE equilibrium is solved using the methodology outlined in Schmitt-Grohe and Uribe (2004), utilizing a second-order approximation of the policy function.

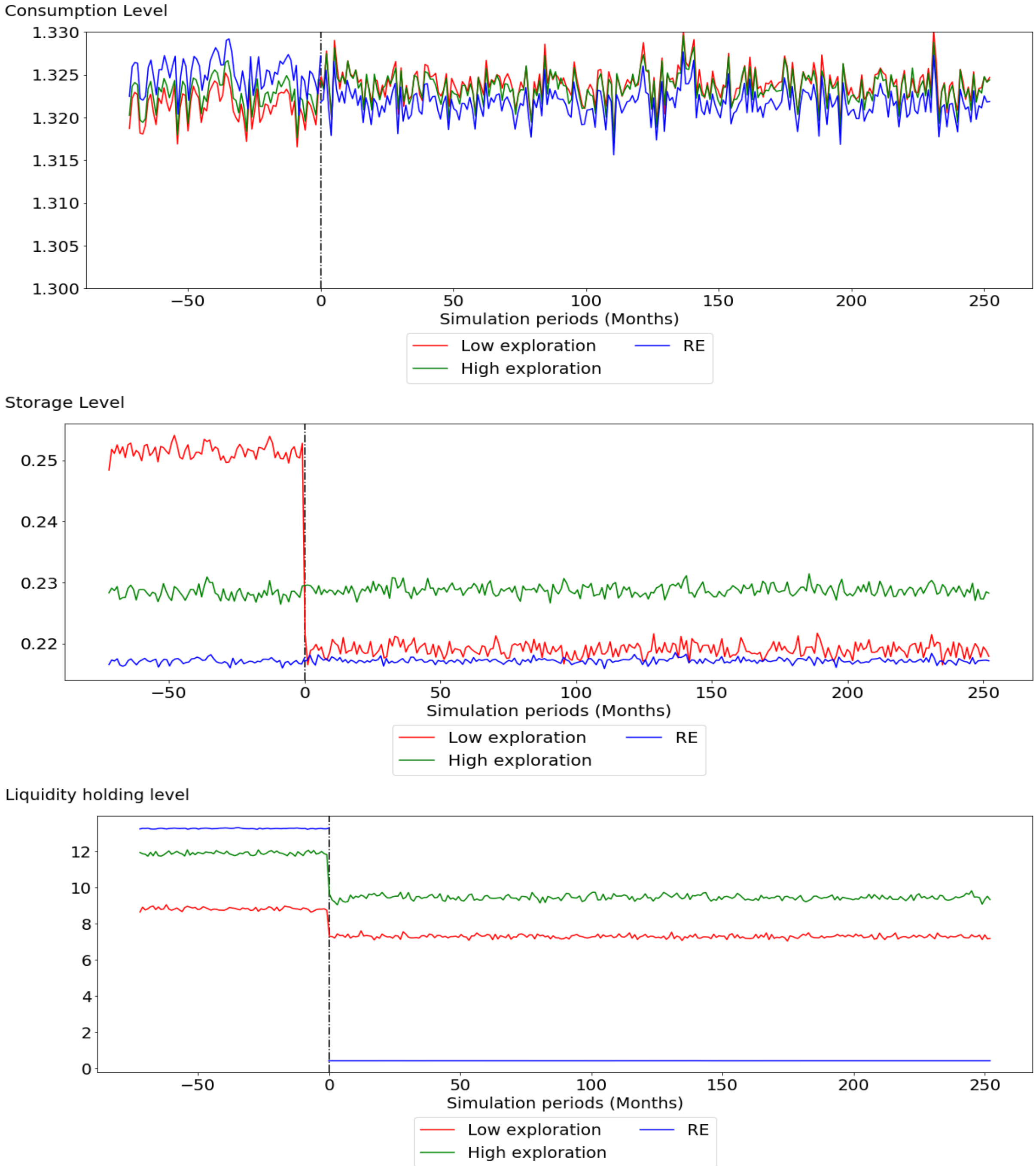
Figure 7: AI vs RE Agents Before and After a Regime Change



Notes:

1. The x-axis depicts simulation periods in months.
2. The y-axis represents endowment level on the top panel, and wealth on the bottom panel.
3. A vertical dashed line at period 0 indicates the occurrence of the regime change. This regime change involves an acceleration of the nominal money supply from a 0% to a 1% daily growth rate.

Figure 8: AI vs RE Agents Before and After a Regime Change



Notes:

1. The x-axis depicts simulation periods in months.

2. The y-axis represents consumption level, storage level, and liquidity holding level, from the top panel to the bottom panel, respectively.

3. A vertical dashed line at period 0 indicates the occurrence of the regime change. This regime change involves an acceleration of the nominal money supply from a 0% to a 1% daily growth rate.

6.5 Discussion

The findings in this exercise demonstrate that AI agents have the ability to adapt their beliefs in response to an accelerating money supply, which has implications on economic transition dynamics and welfare outcomes. The representative AI agent changes its behaviors through interacting with the economic environment. The AI agent makes explorative decisions and observes the associated reward signal. When the current decision-making strategy no longer generates high rewards, the agent adjusts its policy to improve long-term rewards. This aligns with the findings of Cavallo et al. (2017), which demonstrate that private agents are more likely to adjust their inflation expectations in response to price changes in supermarkets rather than relying solely on observed inflation statistics. The direct impact of supermarket price changes on consumers' welfare makes it a more influential signal in shaping consumers' inflation expectations.

It is important to emphasize that, due to their exploratory nature, AI agents do not fully converge to steady-state values, offering a perspective that complements RE models. While exploration entails a trade-off with achieving RE equilibrium, it aligns with aspects of real human behavior, where individuals do not instantly adapt optimally to environmental changes, but instead, learn and adjust through exploration over time. By integrating exploratory behavior and learning from experience, the AI framework, implemented in macroeconomic models, offers an interdisciplinary approach to modeling adaptive economic agents undergoing structural changes. This approach lays the foundation for developing practical models that can be used for policy experimentation and analysis, bridging the gap between theoretical insights and real-world applications.

Nonetheless, implementing deep RL algorithms in policy settings presents several limitations and opportunities for further exploration. A few key points to consider are:

- Slow Learning: Deep RL algorithms have faced criticism for their relatively slow learning and updating processes. The gradual nature of learning in these algorithms may impede AI agents' ability to attain close to the optimal belief within a single generation, especially in complex environments. As explained by Botvinick et al. (2019), the slow learning primarily results from incremental parameter adjustment and weak inductive bias within the algorithm. However, given the rapid evolution of this field, many new deep RL algorithms have been proposed to mitigate this issue and accelerate the learning process. For instance, inspired by Gershman and Daw (2017), deep RL algorithms incorporating episodic memory are under development, enabling AI agents to learn from the experiences gathered by others and potentially reducing the number of required simulation periods. This development highlights the importance of ensuring that adaptive economic agents have access to relevant experiences, enabling them to better adapt to welfare-enhancing changes.
- Utility/Reward Design: Implementing the regime change experiment presents a significant challenge: designing the change as a minor shift in the nominal money supply makes it difficult for AI agents to notice and adjust. This challenge arises primarily because the change in rewards between the two regimes, while present, is relatively small. Future studies should focus more on improving this reward signal mechanism, ensuring it effectively signals AI agents to adjust their beliefs. This aspect is highly pertinent to policy. Policymakers seeking

to accelerate economic transitions need to understand the reward signals that effectively motivate adaptive agents to change their behavior.

- Estimation: Incorporating the exploration mechanism helps integrate theoretical human-like behaviors, leading to noticeable differences between agents' behaviors. However, a crucial unaddressed aspect is aligning parameters with real data or actual human behaviors. Addressing this would make the quantitative implications of exploration more tangible and greatly enhance their applicability in policy analysis.

7 Conclusion

In this paper, I integrated an AI framework into a simple dynamic stochastic general equilibrium model to capture adaptive behaviors of a representative economic agent, drawing on insights from neuroscience and psychology. Using a deep RL approach, the model demonstrated how agents explore alternatives, balance competing objectives, and adjust strategies in response to changes in the nominal money supply. The primary aim was to illustrate the effectiveness of the deep RL framework within a scalable general equilibrium model, showcasing its ability to model an artificial agent that adapts to structural changes through exploration. This work contributes to the existing literature by offering a structured framework and deeper insights into how agents with bounded rationality respond to structural shifts.

Both AI agents adjusted their behavior after a structural change, though they employed different allocation strategies, resulting in distinct outcomes in aggregate inflation and welfare. Specifically, after the increase in nominal money supply, inflation rises to 1% in the high-exploration economy, while in the low-exploration economy, it stabilizes around 1.5%. Exploration not only affects the magnitude of the decisions made by AI agents but also determines which specific decisions are adjusted during a regime shift. The low-exploration AI agent modified both its storage position and liquidity-holding decisions, while the high-exploration AI agent focused primarily on adjusting its liquidity-holding decision. As a result of differences in storage adjustments, the low-exploration agent accumulated 0.6% less wealth than the high-exploration agent in the new regime.

I demonstrated that while the agents' beliefs adjust toward those of an RE agent, they do not fully align due to their exploratory nature. However, this suboptimal belief (measured by comparison with the RE belief) is offset by the AI agents' ability to adapt to regime changes, resembling how humans learn and make decisions in real life.

The findings from this study underscore the utility of the deep RL framework as a valuable tool for modeling artificial agents within an economy undergoing structural changes, while also capturing differences in how economies transition to new states and the resulting impact on overall welfare. The incorporation of the exploration mechanism provided a theoretical, human-like approach to learning and adapting to changes. To enhance the reliability of quantitative predictions for policymakers, future research should focus on anchoring the exploration parameter through real data or actual human behaviors.

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`CENTRAL BANK DIGITAL CURRENCY: THE CASE OF VIETNAM

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Abstract

In recent years, digital currency has emerged as a good candidate to replace bank notes. Many countries around the world have begun to study the issuance of digital currency. As a country with high economic openness, Vietnam needs to monitor new developments and study the implications closely. This paper analyzes several aspects of digital currency and the possibility of issuing digital currency in Vietnam.

Keywords: Central bank, cryptocurrency, digital currency, monetary policy

INTRODUCTION

The development of private digital currencies using blockchain and distribution ledger technology, such as Bitcoin have attracted great attention from public and policy makers. These new types of money are raising crucial questions for central banks, financial system and the economy. Such as what will happen to the demand for cash if private digital currencies are used widely to make payments? Thus, it is necessary for central banks to analyze the impact of these development on the role of central banks, monetary policy, financial system, and the economy. More importantly, central banks should consider whether or not to issue their own digital currency that can be used by the general public to make payments. A number of central banks have plan to issues their own digital currencies, which is called "central bank digital currency - CBDC", to the general public or financial institutions. However, so far, no central bank has issued CBDC.

As a central bank of Vietnam, the State Bank of Vietnam (SBV) has not accepted cryptocurrencies as a currency and a legal means of payment. In addition, the SBV also asked credit institutions not to supply any types of transactions related to cryptocurrencies to ensure compliance with regulations about anti-money laundering and forex management. However, a research group was established to study and propose policies to manage virtual assets and cryptocurrencies. At the moment, the SBV has no plan to issue CBDC, however, a study of the development of CBDC in the world is necessary and important for the SBV to have appropriate policy to response to changes in the world financial and banking industry.

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The rest of the paper is organized as follows. In the next section, the paper gives a definition of CBDC. In section 2 is Vietnam's monetary and financial system: Overview and current challenges. a number of advantages and disadvantages of CBDC. Section 3 presents Vietnam's CBDC policy and development status. Section 4 analyse the social impact and public perception of issuing CBDC. Section 5 analyse key challenges and debates surrounding CBDC implementation in Vietnam. Section 6 is conclusion.

1. What is central bank digital currency - CBDC?

Digital currency is not a new concept for central banks, with function of currency issuance, central banks issue currency in two forms physical central bank notes and electronic reserves. Anyone can hold and use central bank notes, while reserves are available only to selected financial institutions, mostly commercial banks. Recent technological developments have led to suggestions that central banks could consider providing digital currency to the public through centralized accounts (account-based) on its books or decentralized technology (DLT).

There is a huge literature on CBDC, notably Bech and Garratt (2017) who define CBDC is a currency issued by central banks in electronic form, widely accessible and allows to make payments without intermediaries. Meaning, Dyson, Barker, and Clayton (2018) defined CBDC is any electronic, fiat liability of a central bank that can be used to settle payments, or as a store of value. Kumhof and Noone (2018) give a comprehensive definition of CBDC, according to which CBD is electronic central bank money that (i) can be accessed more broadly than reserves, (ii) potentially has much greater functionality for retail transactions than cash, (iii) has a separate operational structure to other forms of central bank money, allowing it to potentially serve a different core purpose, and (iv) can be interest bearing. Prasad (2018) simply defines CBDC is fiat currencies issued by central banks in place of, or as a complement to, physical currency (banknotes and coins). Barrdear and Kumhof (2021) refer CBDC to a currency that is universal access, electronic, national-currency-denominated and interest-bearing.

The definition of CBDC closely relate to how central banks will issue CBDC. There are two methods that central banks could issues CBDC which is being discussed in the literature (i) account-based CBDC and (ii) DLT-based CBDC.

(i) With account-based CBDC, individuals, firms and organizations have an account recorded by central banks and transactions were made through this account. As such trading with account-based CBDC would quite similar to today's transaction between agents through account at commercial banks, accept accounts would be held with central banks. Central banks would ensure settlement after verification of the payer's authority to use the account, sufficient funds, and authenticity of the payee's account. One important benefit of an account-based CBDC is that CBDC trading could be practically instantaneous and costless. In addition, central banks can monitor and control all transactions in the economy, thereby limiting money laundering activities.

(ii) With DLT-based CBDC, transaction can be made directly between the payer and the payee (peer-to-peer) without the need for a central intermediary. Under this system, the involvement of central banks or any other clearinghouse for validating payment transactions is not necessary because of some form of DLT, the technology behind Bitcoin and other private digital currencies. However, in contrast to Bitcoin and other digital currencies, central banks would determine the supply of CBDC, which would be fixed in nominal terms and serve as legal tender. Moreover, the central bank could establish transparent procedures for incorporating appropriate updates to the DLT software—a challenge that has proven to be difficult in the case of digital currencies. The most advantage of the DLT-based CBDC is anonymity as cash transaction since central banks do not involve into transaction process.

To that end, in this paper CBDC is defined as an account-based digital currency issuing by central banks to general public, having three main functions of cash, medium of exchange, store of value, and unit of account.

2. Vietnam's monetary and financial system: Overview and current challenges

Vietnam's monetary and financial system is centered on the State Bank of Vietnam (SBV), which is the country's central bank and primary regulator of the banking sector. The SBV is responsible for issuing the national currency (the Vietnamese đồng, VND), managing monetary policy (such as setting interest rates and credit growth quotas), ensuring financial stability, and overseeing payment systems. Vietnam has a mixed banking system including large state-owned commercial banks, joint-stock banks, and foreign bank branches, all regulated by the SBV. Over the past decade, Vietnam's economy has grown rapidly and integrated more with global trade and finance, putting pressure on its financial system to modernize and expand access.

Despite progress, Vietnam faces several challenges in its monetary and financial landscape that form the backdrop for CBDC considerations. One major issue is the high prevalence of cash transactions and a large unbanked population. Vietnam remains a relatively cash-heavy economy, especially in rural areas and for small payments, which limits the reach of formal financial services. The decreased use of cash is one of main factors that central banks need to consider when deciding whether to issue CBDC (Bordo & Levin, 2017; Engert & Fung, 2017; Khiaonarong & Humphrey, 2019; Mancini-Griffoli et al., 2018). One of the main functions of the SBV is issuing and maintaining the value of Vietnamese dong (VND). Different from developed countries, the use of cash in Vietnam tends to increase as the ratio of cash in circulation to GDP is still quite high, increasing from 11.8% in 2000 to the 18.89% in 2023.

Improving financial inclusion is therefore a national priority – bringing more citizens into the banking system or providing them with low-cost digital payment options. (In fact, the government approved a national financial inclusion strategy in recent years.) A CBDC has been theorized as a tool that could potentially aid financial inclusion by offering a digital means of payment accessible to anyone with a mobile device, without needing a full bank account. This could complement Vietnam's existing efforts like mobile money services (e.g., the SBV has piloted mobile wallet/payment programs to extend services to remote areas).

Another challenge is the fast-growing but *under-regulated* market of cryptocurrencies and digital assets in Vietnam. The Vietnamese public has shown avid interest in crypto – data from 2021-2022 ranked Vietnam among the top countries globally for cryptocurrency adoption (about 21% of the population owned digital assets, one of the highest rates in the world). Vietnam also ranked third worldwide in realized crypto gains in 2023 (around $1.2 billion). This enthusiasm, however, stands in contrast to the official legal framework: Vietnam currently does not recognize cryptocurrencies as legal tender or official payment methods, and the use of Bitcoin and similar crypto for payment has been explicitly banned since 2018. Nevertheless, people continue to trade and hold cryptoassets as investments, and many Vietnam-based blockchain startups register overseas due to legal uncertainty. This situation presents a regulatory and monetary policy challenge: how to manage a burgeoning digital asset market and *cryptoization* risk (i.e., private digital currencies potentially competing with the đồng) without stifling innovation. A CBDC could be seen as part of the answer, by providing a state-sanctioned digital currency and possibly integrating with licensed digital asset platforms.

Vietnam's broader financial system also contends with issues such as: maintaining currency stability (the SBV actively manages the đồng's value and has at times had to sell foreign reserves to stabilize it), controlling inflation (which has been moderate in recent years, around 3-4%), and modernizing its payment infrastructure. The government has a strong policy push for a "cashless economy" and e-government services. Under the e-Government and Digital Transformation Strategy, Vietnam aims to digitize many aspects of the economy, and the SBV has promoted non-cash payment methods, such as QR code standards, interbank quick transfer systems, and mobile payments. In this context, exploring a digital form of the national currency aligns with Vietnam's strategic vision of embracing the Fourth Industrial Revolution and the digital economy. However, any such innovation must be balanced against risks of cyber security, money laundering, and potential disruption to the banking sector.

In summary, Vietnam's monetary system is on a modernization path, led by the State Bank, but grappling with *inclusion gaps*, *crypto-fueled informality*, and the need for more efficient payment channels. These challenges create both the motivation and the cautious tone behind Vietnam's approach to CBDC – seeing it as a potential catalyst for positive change, yet being mindful of the risks and the readiness of the current financial system.

3. Vietnam's CBDC policy and development status

Vietnam's journey toward a central bank digital currency began in earnest in 2021, when the government made a notable policy decision to task the State Bank of Vietnam with researching and piloting a CBDC. On June 15, 2021, Prime Minister Phạm Minh Chính approved *Decision No. 942/QĐ-TTg* as part of a broader e-Government development strategy. This directive explicitly instructed the SBV to "research, develop and pilot the use of virtual money" (a term essentially referring to a CBDC) based on blockchain technology, by 2023. The emphasis on blockchain suggests the government's interest in leveraging distributed ledger technology for the CBDC, in contrast to a purely centralized database approach. This move represented a turnaround in Vietnam's stance on digital currency; after years of banning crypto in payments, the authorities acknowledged the need to proactively explore a state-backed digital currency in step with global trends. Vietnamese officials and experts noted that "digital money is an inevitable trend" and that a pilot would help the government understand the pros and cons of different CBDC models, informing appropriate regulatory mechanisms.

Following the 2021 mandate, the SBV and other agencies undertook preliminary research. Throughout 2022 and 2023, Vietnam's CBDC project remained in a research and development phase, with no public launch of a pilot yet. Reports indicate that Vietnam has been slower than some regional peers, and as of early 2023, "little progress" had been made publicly on the CBDC beyond internal studies. By the original 2023 target, SBV had not issued any pilot CBDC to the public, suggesting the timeline has extended. Nonetheless, work has been ongoing behind the scenes. For example, in late 2022, the *RMIT Fintech-Blockchain Conference* in Ho Chi Minh City featured discussions on CBDC and its implications for Vietnam, indicating scholarly and institutional engagement with the topic. SBV officials have also collaborated with international partners on capacity-building; a "training course" on CBDC for the SBV was noted on the central bank's website, likely in partnership with organizations like the IMF or World Bank who have been advising many developing countries on digital currency design.

In 2023 and 2024, Vietnam's focus expanded to establishing a broader legal framework for digital assets, which complements the eventual rollout of a CBDC. The government formed committees to study not only CBDC but also cryptocurrency regulation. By March 2025, the Ministry of Finance, in coordination with the SBV, was finalizing a proposal to pilot a digital asset exchange in Vietnam. This proposal, requested by the Prime Minister, aims to create a controlled environment for trading cryptocurrencies and other virtual assets under state oversight. Although this is about crypto exchanges, it demonstrates Vietnam's holistic approach: before a CBDC goes live, the ecosystem of digital assets and fintech needs a regulatory backbone. Officials have stressed that digital assets are a "complex and new issue" and that Vietnam must move to transparently manage them for socio-economic development. The envisioned pilot exchange would be operated by licensed entities under state management, thereby protecting investors and reining in the risks of the currently unregulated crypto market. In tandem, the Finance Ministry has been drafting rules to allow Vietnamese enterprises to issue tokens (a sort of *digital fundraising*), again indicating a drive to catch up with global fintech trends while ensuring these activities are anchored in Vietnamese jurisdiction.

Where does the CBDC itself stand as of 2025? The SBV has reportedly conducted research and perhaps even engaged in some proof-of-concept projects, but no official pilot deployment to the public has been announced yet. Some sources suggest Vietnam considers itself to be in a "pilot phase" insofar as the directive to pilot is active, but this likely means internal pilots or preparatory work rather than a live CBDC in circulation. The State Bank governor and other policymakers have been cautious, likely needing to first amend laws to authorize a CBDC issuance and to ensure the technical infrastructure and cybersecurity measures are in place. Dr. Bùi Duy Tùng of RMIT Vietnam noted that significant regulatory reform would be required for Vietnam to issue a CBDC – the legal tender laws currently recognize only physical currency (notes and coins) and bank account money, so they would need updating to include digital currency. This legal groundwork is presumably underway, in consultation with international bodies; as Dr. Tùng pointed out, Vietnam would also want to ensure any CBDC design meets the expectations of institutions like the IMF and World Bank to maintain international confidence.

There have been public-private collaborations indirectly supporting CBDC development. For instance, Vietnam's tech community and financial academia are contributing through research and conferences (as seen with RMIT University's initiatives). The Vietnam Blockchain Association has been active in advising on blockchain adoption and likely engages with regulators on CBDC-related tech matters. It's also notable that Vietnam has been in dialogue with other central banks and organizations. The Asian Development Bank (ADB) and others have supported Vietnam's financial inclusion and digital finance projects, which intersect with the goals of a CBDC. While we have not seen a sandbox pilot of a CBDC yet, it would not be surprising if Vietnam soon partners with a major tech firm or a multilateral agency to run a contained CBDC experiment (for example, testing an interbank stablecoin or a limited retail CBDC for government transfers) as a next step.

In summary, Vietnam's current policy on CBDC is one of *measured exploration*. The government's intent to launch a CBDC pilot was clearly stated in 2021 and reaffirmed by experts in subsequent years, and Vietnam is building the legal and institutional scaffolding (such as crypto exchange regulations and fintech laws) that would allow a CBDC to function in a safe environment. However, the timeline appears to have been extended beyond 2023, reflecting a cautious approach. No official CBDC is live yet in Vietnam, but groundwork in the form of research, capacity building, and related regulatory development is actively ongoing. The coming years (2025-2026) may see more concrete pilot programs from the SBV, possibly starting in a limited scope (e.g. a sandbox for interbank CBDC or a retail pilot in a controlled setting), once the supporting legal framework is in place.

4. Social impact and public perception

The introduction of a CBDC in Vietnam would have wide-ranging social implications, as it may transform how citizens interact with money and financial services. One anticipated benefit is greater financial inclusion, especially for underserved communities. Socially, a CBDC could empower people in rural areas or the urban poor who currently lack bank accounts. With a CBDC, all that is needed is a digital wallet (possibly tied to a mobile phone number); Vietnam has high mobile penetration, so this could bring many into the formal financial system. This inclusion could have positive social outcomes: safer money storage (reducing the risk of theft of cash), easier receipt of government payments or remittances, and access to digital marketplaces. Women, low-income households, and other marginalized groups might particularly benefit if the CBDC is designed for simplicity. As noted by Vietnamese academics, a CBDC that works offline on simple devices could allow people even in remote regions to transact at low cost, which is a powerful tool for inclusion.

However, social acceptance of a CBDC is not guaranteed. Public perception and trust will be crucial. Vietnamese society currently has a strong comfort with cash – culturally, many still prefer its tangibility and anonymity. To persuade users to adopt the digital đồng, the authorities will need to build trust in its reliability and security. If people fear that the government could monitor all their transactions, some may resist using the CBDC for anything beyond small amounts, sticking to cash for privacy. Indeed, privacy concerns have already been noted: one study highlighted a "big concern from the Vietnamese public regarding privacy" if a CBDC were to replace physical cash. Cash offers anonymity and freedom; a CBDC could be seen as undermining that, which might be socially sensitive. To address this, the SBV might incorporate privacy-enhancing features (for instance, not collecting personal data on small transactions or using anonymized IDs for low-tier wallets). Communicating these safeguards will help mitigate fears. The design could even allow *pseudo-anonymity* for low-value transactions (similar to how the ECB considers small offline payments in digital euro to be anonymous like cash). Nonetheless, more surveillance is inherent compared to cash – that's a social trade-off people will evaluate.

Another social dimension is digital literacy and readiness. Not everyone is comfortable with digital apps or smartphones, especially the elderly or less educated segments. There may be a learning curve or reluctance among such groups to use a CBDC app. The government would likely need to conduct public education campaigns and possibly enlist mass organizations to help train users (in Vietnam, organizations like the Women's Union, Farmers' Union etc. often help disseminate new initiatives). Ensuring the user interface is extremely simple and in Vietnamese (and maybe minority languages as needed) would be important. Social trust also extends to *trust in technology* – if there are any early glitches or reports of theft/fraud, they could cause disproportionate fear. Thus, a careful, small-scale pilot (perhaps in a city or with specific user groups) can demonstrate the system's safety before a wider rollout.

The CBDC's social impact also ties into consumer habits and business practices. For urban youth who are already using MoMo, ZaloPay, or bank apps, a CBDC might just be another wallet – possibly even integrated into those same apps. This group is likely to be early adopters, especially if there are incentives (e.g., merchants offering discounts for CBDC payments, or the government giving a small bonus for trying the CBDC). For small businesses and street vendors, the social change could be significant: if digital payments penetrate deeper via CBDC, some might worry about losing out (for instance, those who prefer cash to avoid taxes might resist digital tracking). Over time, though, if the social norm shifts towards digital payments, even cash-centric businesses could feel pressure to accept the CBDC to cater to customer preferences. The state might encourage this by making government transactions digital – imagine paying public school fees or hospital bills via CBDC – which in turn normalizes it.

Financial behavior could shift socially as well. People might start keeping a portion of their savings in CBDC wallets (if they view it as as good as cash). This could reduce money kept "under the mattress," improving security for households. It might also prompt more responsible financial habits, as digital records can help with budgeting and tracking expenses (assuming user apps provide such features). On the other hand, ease of digital spending sometimes leads to overspending (since the psychological friction of parting with cash is removed). These behavior changes are documented in studies of mobile money and digital finance adoption in other countries.

One potential social controversy is the risk of excluding those who cannot or will not go digital. Even with high mobile penetration, there will be some who don't have access to a phone (the very old, or extremely remote communities) or who are disabled in ways that make current digital interfaces hard to use. The government must ensure the CBDC rollout doesn't marginalize these groups – cash should probably remain in circulation for a long time as an alternative. Overzealous pursuit of a "cashless society" could inadvertently disadvantage some citizens. So, a balanced approach is needed, where CBDC is an *option* that's gradually adopted, not a forced replacement in the short term.

Finally, the social narrative around CBDC will matter. If it is pitched as a nation-building, progressive move, and early adopters (especially educated youth, tech enthusiasts) champion it, it can gain positive momentum. The fact that Vietnam has such a high engagement with cryptocurrencies suggests a sizable portion of society is already mentally primed for digital currencies – they might actually welcome a state-guaranteed one after experiencing the volatility and risk of crypto. This younger cohort might view CBDC as *"cool tech"* or a way Vietnam is joining an elite club of innovators. Their social influence could bring more people onboard. Conversely, if misinformation or skepticism spreads (for example, conspiracy theories about government control), it could hamper adoption. Public trust in the SBV is generally decent, as inflation has been kept in check and the banking system has improved stability, but any misstep could erode confidence.

In summary, the social dimension of CBDC in Vietnam involves ensuring broad and equitable access, building trust by addressing privacy and security concerns, and managing the cultural shift from cash to digital money. Done right, it can enhance inclusion and convenience, fitting into people's lives relatively smoothly (especially if integrated with tools they already use). But authorities will need to be attentive to public sentiment. Early engagement with communities, pilot testing and gathering feedback, and transparent communication about how data is handled will all be key in achieving social acceptance of the CBDC.

5. Key challenges and debates surrounding CBDC implementation in Vietnam

While the potential benefits of a Vietnamese CBDC are significant, there are numerous challenges, debates, and controversies that surround its implementation. These span economic, technical, legal, and ethical realms:

- *Privacy and civil liberties:* Perhaps the most prominent debate globally, and indeed in Vietnam, is about the privacy of CBDC transactions. As noted, Vietnamese citizens value the anonymity of cash, and there is concern that a CBDC could lead to government surveillance of spending. Civil society observers warn that in an authoritarian context, a CBDC might enable authorities to track every transaction and even freeze accounts of dissidents, facilitating financial repression. While the government's intent may be to target criminals (money launderers, tax evaders, etc.), the lack of strong checks and balances raises fears of abuse. The debate here is how to design a CBDC that respects personal privacy to a reasonable extent. Some propose technological solutions like privacy-preserving cryptography, or policy solutions such as strict legal limits on data access. This remains a contentious issue: striking a balance between traceability for law enforcement and privacy for users.

- *Security and resilience:* A critical challenge is ensuring the CBDC platform is secure from hacking and operational failures. A single bug or breach could undermine trust permanently. The technical debate is whether a blockchain-based system is more secure (due to decentralization) or a centralized system is easier to protect (due to controlled access). Experts emphasize the need for rigorous testing and perhaps phased rollouts to iron out vulnerabilities. Cybersecurity capacity in Vietnam will need to be ramped up – this involves not just securing the core system but also educating users on protecting their wallets (preventing scams, phishing, etc.). If people lose money due to hacks or forget passwords without recovery mechanisms, it could create public outcry. So the user experience vs. security trade-off is also debated: for instance, should the SBV enable wallet recovery (which is user-friendly but means the system has some way to override control of funds) or treat wallets like cash (lost key = lost money, which could be harsh for users)?

- *Financial stability and bank disintermediation:* There is an ongoing debate on whether a CBDC will harm banks by taking away deposits. Vietnamese banks are the main channels of credit; if they lose a chunk of retail deposits to CBDC wallets, their funding and lending could contract, potentially slowing economic growth. Some bankers might oppose a widely accessible CBDC for this reason. To mitigate this, proposals include setting a holding limit (each person can only hold a certain amount of CBDC, above which it must be swept into a bank account) or not paying interest on CBDC to keep it less attractive than deposits. The challenge is designing those limits in a way that doesn't overly constrain usefulness. The policy debate extends to whether CBDC could inadvertently enable *digital bank runs* – in a crisis, people might convert bank deposits to CBDC with a few clicks if they perceive it safer, thereby worsening a bank's run. The SBV will have to plan safeguards (like temporary limits) for such scenarios.

- *Technological choice and interoperability:* Within technical circles, there's debate on which technology Vietnam should use – an existing blockchain platform, a custom solution, etc. Using proven technologies can reduce risk, but Vietnam might want domestic control and customization. Compatibility with other systems (both domestic, like existing payment networks, and international, like other CBDCs or payment systems) is a debated priority: some argue cross-border functionality from the start would be beneficial (for tourism, remittances), others say that complicates things early on and domestic use should be the focus first. Scalability vs. decentralization is another technical debate – e.g., a fully decentralized model might not scale as well or might be slower (not ideal for point-of-sale payments). Experts will need to reach consensus on what design philosophy aligns with Vietnam's needs.

- *Necessity and public demand:* There is also a fundamental question asked in policy debates: *Does Vietnam really need a retail CBDC?* Critics might point out that digital payment adoption is already rising thanks to private e-wallets and mobile banking; they may argue that improving those (and expanding banking services) could achieve the same goals without the cost and risk of CBDC. Proponents counter that a CBDC offers unique advantages – it's legal tender, doesn't require a bank account, and is safer (no default risk). This debate touches on opportunity cost: the government has finite resources and attention, so is focusing on CBDC the best use of time compared to other financial reforms? The current approach suggests Vietnam believes it's worth exploring, but the debate isn't completely settled even within policy circles.

- *Monetary policy implications:* Another debated topic in academic circles is how a CBDC might change the tools of monetary policy. Some theorists (like those referenced by BIS) argue it could enhance control (as previously noted, faster transmission). Others worry about new complexity, like how to set interest rates on CBDC if at all, and how to manage the central bank's balance sheet when potentially directly interfacing with millions of individuals. Vietnam's context of a partially dollarized economy (people holding USD or gold as savings) could also figure in debates: would a CBDC encourage people to hold more đồng instead of dollars/gold (thus strengthening monetary sovereignty), or could it, if not managed, become something people swap into USD-backed stablecoins if they can? There's a sovereignty angle: ensuring the CBDC is attractive enough that people prefer it over unofficial alternatives for store of value.

In conclusion, Vietnam faces a complex landscape of challenges and lively debates as it charts its path to a CBDC. None of these challenges are insurmountable, but they require careful consideration. Vietnam's advantage is that it is not the first mover – it can watch and learn from countries that have launched pilots or actual CBDCs, and adopt best practices while avoiding pitfalls . The discourse involving scholars, technologists, bankers, and the public will shape a CBDC that, if it comes to fruition, reflects a balance between *innovative progress and prudent governance*.

6. Conclusion

The main functions of central banks are issuing currency, implementing monetary policy, and promoting safety of financial and payment system. Recent technological innovations have changed the way the financial system works, creating new payment methods and new types of virtual currencies such as Bitcoin. These changes have attracted the attention of central banks in issuing its own digital currency. Many central banks are actively researching about CBDC (Sweden's central bank, People's bank of China, Bank of China). However, there are also a number of central banks no longer pursuing CBDC (Australia, Denmark, European Central Bank, New Zealand, Switzerland).

Currently, no central bank has yet to issue digital currency to the public and some central banks (such as Reserve bank of Australia, Central bank of Denmark, European Central Bank, Reserve bank of New Zealand, Swiss National Bank) no longer pursuing CBDCs. However, CBDC is very promising and need to have careful and comprehensive analysis of the benefits and risks that may arise from CBDCs. To effectively carry out its own main functions in a changing environment, the SBV, as the central bank of a small developing country, need to monitor new developments and study the implications closely.

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