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The role of technology in business-to-consumer e-commerce: Evidence from Asia

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THE ROLE OF TECHNOLOGY IN BUSINESS-TO-CONSUMER E-COMMERCE

EVIDENCE FROM ASIA

Jong Woo Kang, Tengfei Wang, and Dorothea Ramizo

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Jong Woo Kang, Tengfei Wang, and Dorothea Ramizo

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ABSTRACT

The business-to-consumer (B2C) online commerce landscape is changing rapidly, supported by the technological innovation. However, its diffusion remains concentrated in developed and large economies and is creating a digital divide that excludes small and medium-sized enterprises and people with limited means. The coronavirus disease (COVID-19) pandemic exposed an urgent need to close the divide, both within and across countries. This paper explores disparities in B2C online commerce revenues among selected Asian economies by investigating the role of technology adoption in B2C sales online. Using proprietary panel data to ensure comparability of B2C online commerce across countries and years, the study investigates empirically the possible drivers of B2C online commerce growth. This paper yields important insights for policy makers and businesses and provides evidence that internet access and speed, online security, and financial inclusiveness matter in facilitating internet retail sales. Governments should consider these as important issues in building an enabling environment that will help B2C online commerce adapt to the post COVID-19 world and ensure that innovations create opportunities for all.

Keywords: broadband, e-commerce, financial inclusion, technology

JEL codes: F13, F14

I. INTRODUCTION

Electronic commerce (e-commerce) has been hailed as a disruptive technological innovation that has radically transformed business-to-consumer (B2C) interactions in both domestic and cross-border retail sales by providing advanced tools for building audience engagement, reaching customers, improving sales, and improving efficiency and productivity. The internet retail landscape is again transforming with the advent of mobile commerce (m-commerce), the buying and selling of goods and services through wireless handheld devices such as smartphones and tablets. This puts shopping literally at consumers' fingertips while creating unprecedented opportunities for businesses and signaling a new era of growth in online retailing. These developments are made possible by the rapid innovation in information and communication technology (ICT), particularly rapid advancements in internet technology and tablets and smartphones. However, as fast as these advances occur, they have been limited largely to developed and large economies.

While the earlier work by the Asian Development Bank and United Nations Economic and Social Commission for Asia and the Pacific (2018) and the United Nations Economic and Social Commission for Asia and the Pacific (2019) provide descriptive analysis on e-commerce and technology, few studies have empirically investigated the role of technology adoption in online retail growth, particularly in the context of Asia, even as the region's growth prospects in internet retail sales have been promising. This paper aims to fill this crucial gap in the literature on the relationship between technology adoption and B2C online commerce. Using proprietary panel data on Asia's B2C online commerce to ensure comparability across countries and years, the study attempts to answer two specific research questions: First, within countries, what are the determinants of B2C online commerce in general and its segments in particular (i.e., m-commerce, domestic and foreign or cross-border internet retail sales)? Second, what role does adoption of ICT infrastructure, in particular, play in driving B2C online commerce? Rigorous empirical investigation of these questions can provide important insights about the implications of the digital divide on B2C online sales, adding to knowledge on how to build an inclusive digital economy for all.

The rest of the paper is organized as follows. Section II reviews existing literature on B2C online commerce and is followed by a discussion on data collection and variables in section III. The model specification and estimation techniques are presented in section IV. The main results are discussed in section V, while section VI concludes.

II. REVIEW OF RELATED STUDIES

This section examines our two research questions by reviewing country studies on internet retail sales, including the most recent literature on the rapidly evolving B2C online commerce landscape. Because B2C online sales are part of consumer spending, studies on B2C online commerce that incorporate determinants of consumer spending are also reviewed.

A. Country-Level Internet Retail Studies

The development of online commerce driven by rapid technological innovations during the 2010s has received attention in numerous research works. The field has been investigated using different theoretical lenses and levels of analysis. Works have focused on internet-based selling adoption, whether that be to individuals, between firms, or at the country level. Studies have looked at flows across online retailing electronic channels or the hardware alternatives that consumers use to shop online (e.g., computers, laptops, smartphones, tablets, and internet-enabled television) and e-channel touch points or software components such as mobile shopping apps.¹

Several studies have identified the enablers and disablers of e-business adoption involving firms across developing Asian countries. Tan et al. (2009) merges principles from diffusion of innovation theory and the security and costs considerations associated with e-commerce technologies. A survey on a sample of small and medium-sized enterprises (SMEs) in the south of Malaysia underscores the importance of relative advantage, complexity, and security on SME e-commerce adoption.

Another study highlights the role of perceived benefits, costs, and organizational culture in internet adoption of Malaysian SMEs (Alam 2009). Kurnia et al. (2015), a quantitative study of Malaysia's grocery SME retail sector, examines the influence of organizational, industry, and national readiness and environmental pressure on the adoption of diverse e-commerce technologies. The study finds that organizational and national readiness have different influences across diverse e-commerce technologies, and that the influence of industry readiness is insignificant.

Using survey data, a study on e-commerce adoption by SMEs in Indonesia finds that perceived benefits, technology readiness, and owners' innovativeness, information technology ability, and experience all determine how Indonesian SMEs adopt e-commerce (Rayahu and Day 2015). Another study on Indonesian SMEs uses an integrated framework to examine the relationships between contextual factors that influence e-commerce adoption. It finds organizational context to be the most significant predictor of e-commerce adoption, followed by technological and environmental contexts (Hadi Putra and Santoso 2020).

At the macroeconomic level, many factors can affect B2C online commerce growth. That B2C online commerce has far-reaching impacts across economic sectors is amplified by the COVID-19 pandemic, which has forced everyone from households to governments and multinational firms to transfer their activities and operations online in a matter of months. Households have come to rely on e-grocery and food delivery platforms to shop for basic needs. Banks are fast-tracking digital banking solutions such as mobile apps with e-payments and e-wallet functionalities. Hospitals have resorted to telemedicine or e-consultations. SMEs are putting up websites and implementing e-commerce solutions because a compelling online presence is now the new normal for profitable business operations.

The revolutionary changes in the B2C online landscape makes it more crucial than ever to understand the factors driving this transformation at the macroeconomic level. However, access to quality and consistent technology and e-commerce national statistics that are comparable across countries and time periods remains a challenge. This means that country-level technology studies typically suffer from limited availability and constrained access to appropriate countrywide data. As a

¹ Some examples are Lestari 2019, Kurnia et al. 2015, Ueasangkomsate 2015, Rayahu and Day 2015, Kabango and Asa 2015, Alyoubi 2015, McLean et al. 2020, Rana et al. 2019, Verkijika 2018, Chau and Deng 2018, Ahuja and Khazanchi 2016.

result, few studies have examined the country-level variables that may play a role in e-commerce adoption in some economies. National factors such as government policy on e-commerce legislation are seen to affect the extent of e-commerce adoption across 10 different countries in Gibbs, Kraemer, and Dedrick (2003). Another study uses national indicators of online commerce activities to find that ICT laws, higher education, and innovation capacity influence a country's online commerce transactions (Boyer-Wright and Kottemann 2009).

Meso et al. (2009) applies historical data to highlight a significant relationship among national information infrastructure, governance, and socioeconomic development among developing economies. Evidence has also shown that at the nascent stage of e-commerce adoption, national factors such as government policies, effective legal environment, and compatible sociocultural infrastructure have been compelling drivers of e-commerce adoption in major global economies (Zhu and Thatcher 2010). Meanwhile, Martinez and Williams (2010) employ institutional theory and entrepreneurship theory to investigate the role of ICT adoption in e-commerce across countries. Drawing on a sample of 80 economies, the authors find that institutional quality plays a critical role in developing economies, where it is a powerful driver for both the basic and more advanced technologies that underpin online commerce.

Ho, Kauffman, and Liang (2011) employ a hybrid growth theory approach as the theoretical basis for examining exogenous and endogenous factors that influence e-commerce growth within countries. These factors include financial card penetration, adult literacy, telecommunications investment, internet user penetration, secure server penetration, international openness, population density, and the availability of venture capital. The study provides empirical evidence of the direct impact of technology adoption indicators such as internet user penetration, telecommunications investment, and international openness on e-commerce growth.

None of these research work considers that the impacts of technology adoption measures and financial readiness may vary depending on where e-channel B2C online sales arise (e.g., on computers, laptops, tablets, or smartphones) or where the sales originate (e.g., domestic or foreign). Nevertheless, several studies have attempted to investigate m-commerce adoption and cross-border online sales by separating them out from B2C online commerce in general.

For instance, McLean et al. (2020) examine whether there is a difference in the attitudes and actual behaviors of consumers toward retailers' m-commerce mobile applications between initial adoption and their later, continuous use. The study finds that customer attitudes toward the app at the initial phase of adoption is driven by subjective norms, but this does not happen at the usage phase. Meanwhile, both adoption and usage phases are affected by perceptions of ease of use and usefulness. Moreover, the strength of variables affecting customer attitudes changes from initial adoption to usage such that, for instance, enjoyment and customization become stronger as the customer continues to engage in m-commerce. McLean et al. (2020) discuss the previous research, examining determinants of initial mobile app adoption, predominantly through utilizing and extending the Technology Acceptance Model or the Unified Theory of Technology Acceptance and Use. The paper also reviews studies that have explored variables influencing the continuous use of mobile applications.

Consumer interest in buying from foreign merchants continues to grow (UNCTAD 2020b). The share of cross-border online shoppers to all online shoppers increased from 17% in 2016 to 23% in 2018. Cross-border B2C e-commerce sales reached \$404 billion in 2018, a 7% rise over 2017. Two recent studies recognize this trend and examine the reasons behind it. Zhu, Mou, and Benyoucef (2019) focus on the influence of product cognition on purchase intention in cross-border e-commerce. The study finds that perceived trust has a full mediation impact, suggesting that

consumers' processing and response in cross-border e-commerce platforms is a sequence from product recognition to platform emotion and from platform emotion to behavior intention.

Han and Kim (2019) sought to identify the underlying mechanism explaining why and how international consumers become aware of opportunities to buy from abroad. The study demonstrates that awareness of a wide range of attributes, including price, product, seller, and processes, strongly inform purchase intentions. It thus validates the relationship among consumer characteristics, information technology use patterns, and consumer awareness that acts as an underlying mechanism of cross-border purchases online.

In summary, while the current literature is rich in studies that use behavioral models to identify factors behind e-commerce adoption by individuals and firms, scant empirical evidence exists on the relationship between technology adoption measures (e.g., internet users penetration, broadband penetration, secure servers, and so on), financial environment readiness (e.g., credit card and debit card penetration) and various segments of country-level B2C online commerce including m-commerce, cross-border internet retail sales, and domestic internet retail sales. The aim of this paper is to fill this gap in literature and understand the role of technology adoption indicators, which reflect the breadth and depth of technology infrastructure for B2C online commerce growth at the country level.

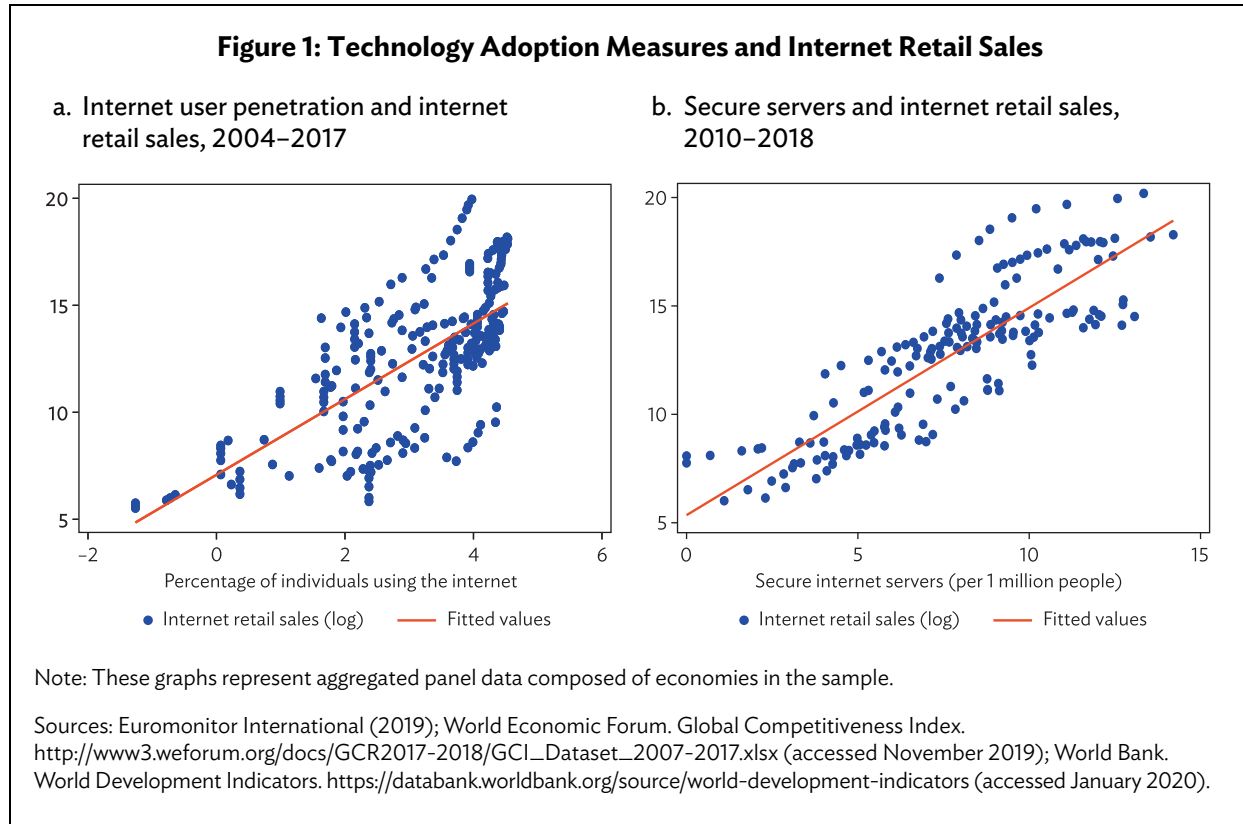
B. The Role of Information and Communication Technology Adoption in E-commerce

Existing literature has identified several possible factors affecting economic growth and B2C online commerce growth, with technology adoption among them (Ho, Kauffman, and Liang 2011; Myovella, Karacuka, and Haucap 2020). Previous research efforts applied different variables to measure the impact of technology adoption and diffusion at the country-level economic performance (Ho, Kauffman, and Liang 2011). The very existence of B2C online commerce relies on technology infrastructure. Given this, installed computing capacity and internet access are proxy measures of technology adoption because consumers and merchants cannot participate in B2C online commerce without them.

Klaus (2017) identifies other technology adoption measures, including broadband internet subscriptions, internet bandwidth, and mobile broadband subscriptions. These are also the primary indicators of internet technology adoption by individuals and firms. Because internet technology adoption is indicative of the size of the B2C online commerce market, potential growth of internet technology adoption stimulates additional development of the B2C online commerce infrastructure (Ho, Kauffman, and Liang 2011). While B2C online commerce is usually associated with internet technology adoption, mobile phones and fixed telephone lines can also facilitate online transactions (WTO 2020).

An extensive body of literature has examined the role of trust, which is associated with perceived privacy and security, in B2C online commerce adoption. Studies have identified concerns on security issues as among the main barriers to the adoption of internet commerce in general and m-commerce in particular (Burroughs and Sabherwal 2002; Chau and Deng 2018; Lee and Wong 2016; Alyoubi 2015; Sarkar, Chauhan, and Khare 2020; Zhu, Mou, and Benyoucef 2019). Hence, the number of secure servers may be a credible proxy to capture firm-level initiatives to supply secure online services to the market or adopt internet-based selling technology (Ho, Kauffman, and Liang 2011). Online retailers, online banking and financial services, and other online service providers employ secure socket layer (SSL) to secure encrypted connections between servers and browsers. Secure servers protect sensitive information such as credit card and personal information by ensuring these

can be securely encrypted and transmitted online. In general, the above discussion argues that internet user penetration, along with other internet technology adoption indicators can represent the demand side of the B2C online commerce market, while secure server penetration can represent its supply side (Figure 1).



C. Factors Affecting Business-to-Consumer Online Commerce

Several studies have also sought to examine the determinants of B2C online commerce from economic growth theory and the consumer spending literature, not just from the technology adoption perspective. Prior studies provide empirical evidence on the positive association between education and the capacity of individuals to use the internet and engage in B2C online commerce activities (Caselli and Coleman 2001; Burroughs and Sabherwal 2002; Pohjola 2003; Ho, Kauffman, and Liang 2011).

Drawing from economic growth theory, Ho, Kauffman, and Liang (2011) and Myovella, Karacuka, and Haucap (2020) both recognize the contributions of e-commerce in weakening the force of geographical boundaries and facilitating trade in goods across borders. These studies conclude that international openness supports knowledge spillovers and technology transfers across borders, leading to technological progress and efficient organization of an economy by paving the way for specialization in producing goods in which a country has a comparative advantage. Ho, Kauffman, and Liang (2011) lend empirical support to the hypothesis that trade openness has a positive impact on B2C online commerce.

Because B2C online commerce essentially represents a portion of consumer spending, determinants of consumer spending are also considered. Several studies find evidence on the relationship between employment and consumer spending (Côté and Johnson 1998). Consumers with high debt-to-income ratios are sensitive to increasing uncertainty, such as unemployment risks, which make them more likely to delay the purchase of consumer durables. Nondurables spending is also sensitive to changes in unemployment prospects. Canonical consumption theory of the life-cycle permanent income hypothesis suggests that consumption is affected by financial as well as human assets. One of the key factors to influence the level of human asset is education acquired.

According to conventional intertemporal consumption model, inflation is another variable affecting consumer spending. Using observations from consumers in the euro area, Duca, Kenny, and Reuter (2018) found that consumers increase their spending when they expect inflation to rise, all other factors equal. This is consistent with earlier results in the empirical literature on consumer behavior. Using comprehensive high-frequency state and local sales tax data, Baker, Johnson, and Kueng (2018) show that shopping behavior of consumers in the United States is strongly associated to changes in sales tax rates. While sales taxes have extensive range of rates and exemptions and are not reflected in posted prices, consumers still alter their spending pattern in many ways. They buy storable goods in bulk before a tax increase and spend more on online and cross-border shopping in both the short and long terms.

III. DATA, METHODS, AND EMPIRICAL ANALYSIS

This section presents our model specification and estimation techniques, data sources, and operational definitions of the variables used. The purpose of this empirical exercise is to understand the determinants of B2C online commerce using pooled ordinary least squares (OLS) and standard panel econometric methods such as fixed effects and random effects models. Each has a different information structure for error terms. By using alternate models, the objective is not to identify which model offers the best fit for the variables but to see what can be learned from each of them as well as robustness of empirical findings. Fixed effects and random effects models with lagged technology adoption variables are also used to address the potential reverse causal relationship between B2C online commerce and relevant technology adoption measures.

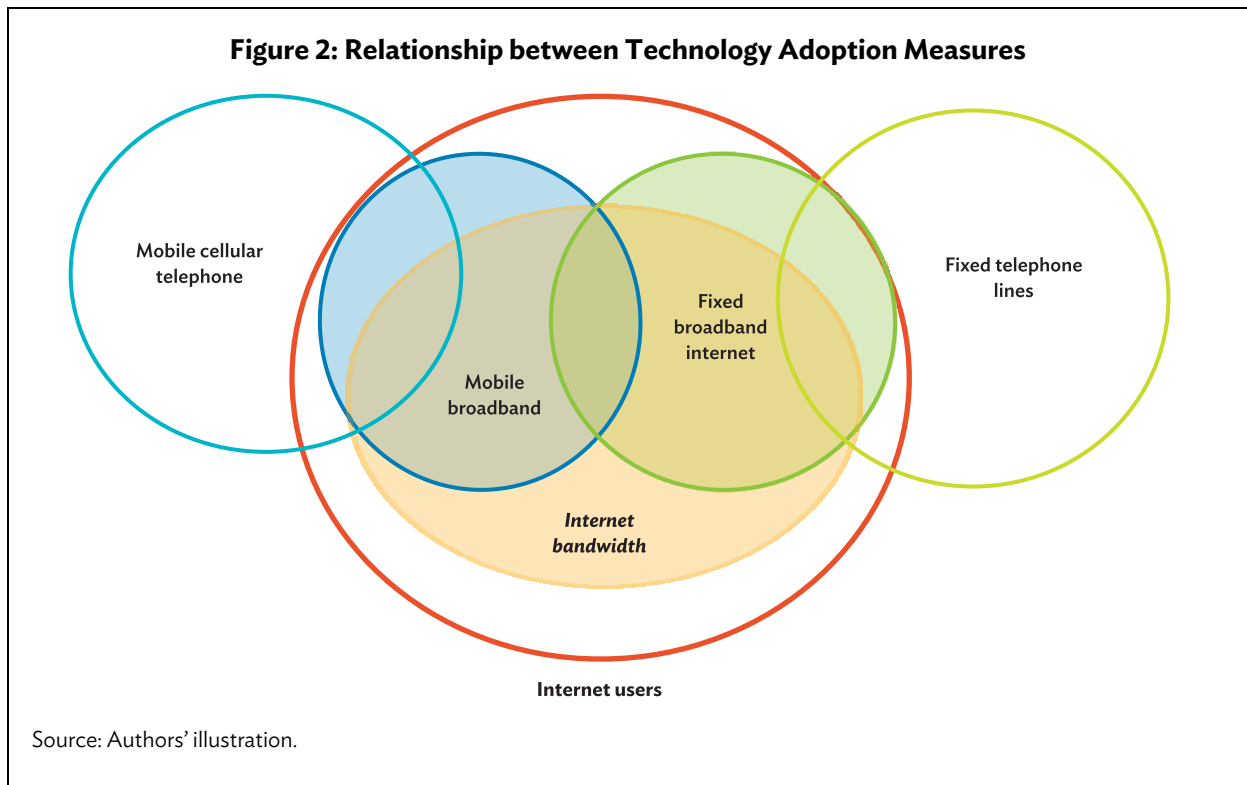
A. Model Specification and Estimation Methodology

Drawing upon the discussion on the previous section on theoretical background and development, the hybrid growth theory approach in Ho, Kauffman, and Liang (2011) is employed to investigate the determinants of types of B2C online retail sales. Literature has identified several socioeconomic variables affecting consumer spending. These are included in the model as control variables because online retail sales form part of consumer spending. A panel model is used to estimate the following specifications:

$$\ln B2C_{it} = \ln Tech_{it} \alpha_1 + \ln server_{it} \alpha_2 + \ln DC_{it} \alpha_3 + \ln \mathbf{Z}'_{it} \boldsymbol{\alpha} + c_i + \epsilon_{1it}, \quad (1)$$

$$\ln B2C_{it} = \ln Tech_{it}\gamma_1 + \ln server_{it}\gamma_2 + \ln CC_{it}\gamma_3 + \ln \mathbf{Z}'_{it}\boldsymbol{\gamma} + c_i + \epsilon_{2it}. \quad (2)$$

In these equations, \mathbf{Z}_{it} includes inf_{it} , tar_{it} , emp_{it} , tax_{it} , $educp_{it}$, and $educs_{it}$; $B2C_{it} = IRS_{it}, MOB_{it}, DOM_{it}$ or FOR_{it} ; and $Tech_{it} = IUT_{it}, FBIS_{it}, IIB_{it}, MBS_{it}, MTS_{it}$ or FTL_{it} , where the dependent variable $B2C_{it}$ represents the different categories of B2C online commerce s of country i at time t . These are internet retail sales (IRS_{it}), mobile internet retail sales (MOB_{it}), domestic internet retail sales (DOM_{it}), and foreign internet retail sales (FOR_{it}). $Tech_{it}$ represents the technology adoption measures based on share of internet users (IUT_{it}), fixed broadband internet subscriptions per 100 population ($FBIS_{it}$), international internet bandwidth (kb/s) per internet user (IIB_{it}), mobile broadband subscriptions per 100 population (MBS_{it}), mobile telephone subscription per 100 population (MTS_{it}), and fixed telephone lines per 100 population (FTL_{it}). Figure 2 illustrates the relationship between these technology adoption measures.



$Tech_{it}$ variables are separately estimated in the model to determine which of these technology adoption measures can serve as proxies for the size of the market in which B2C online retail transactions occur. Meanwhile, the number of secure servers ($server_{it}$) represents online retail technology adoption, reflecting firm-level investments to supply B2C online retail services (Ho, Kauffman, and Liang 2011). Technology adoption measures $Tech_{it}$ and $server_{it}$ are the variables of interest of this study.

Financial environment readiness of B2C online sales is captured by debit cards per 1,000 adults (DC_{it}) and credit cards per 1,000 adults (CC_{it}). These proxy variables are included separately in the model because their pairwise correlation is at the level of 0.85. This relationship reflects prevailing banking practices requiring a bank account to have a debit card for making transactions, while bank

account information is usually one of several requirements for obtaining a credit card. Hence, a credit card holder would also normally have a debit card, explaining the high correlation between the two.

A set of control variables Z_{it} includes well-established socioeconomic factors affecting consumer spending in general to determine whether they remain relevant in understanding B2C internet sales. These are inflation (inf_{it}), employment (emp_{it}), average tax rate (tax_{it}), and primary ($educp_{it}$) and secondary ($educs_{it}$) education levels. Tertiary education is not included because of its high pairwise correlation with credit card ownership (CD_{it}) at 0.83, underscoring the significant role of higher education in obtaining credit cards (Bertaut and Haliassos 2006). Tariff tar_{it} is used as a proxy variable to measure the impact of international openness on internet retail sales.

Country-specific and time-invariant factors that might be correlated with both $B2C_{it}$ and the explanatory set are captured by c_i , while the stochastic error term ϵ absorbs all other determinants of $B2C_{it}$ not explicitly included in the model.

Equations (1) and (2) are first estimated using pooled OLS which does not consider the panel structure of the data. This fails to control the differences across cross-sectional units (countries) and time periods and the unobservables that are related to both the regressors and the regressand or the omitted variable bias. Estimating models (1) and (2) using pooled OLS, however, can give us a sense of the direction of the endogeneity.

In the random effects model, the time-invariant country characteristics c_i is assumed to be neither correlated with the regressors nor with the error term ϵ . Country effects are assumed to be *IID* distributed with a mean of 0 ($c_i \sim IID(0, \sigma_u^2)$). This means that the country fixed effects c_i in equations (1) and (2) are assumed to be *randomly* distributed and no longer needed to be explicitly estimated because they already form part of the now composite error term ϵ . Hence, equations (1) and (2) are estimated without c_i using generalized least squares. Imposing the assumption that country-specific and time-invariant factors are not correlated with the regressors implies that a violation of this assumption would produce inconsistent estimates because of omitted variable bias. These country characteristics include geography, culture, institutions (e.g., regulation), and historical patterns of technology development or path dependence. Literature identifies these factors as important determinants of technology adoption upon which B2C online retailing is built (King et al. 1994; Comin, Dmitriev, and Rossi-Hansberg 2012; Lee, Trimi, and Kim 2013; Stoneman 2004; and Puffert 2003).

In the fixed effects model, the time invariant c_i is assumed to be potentially correlated with the explanatory variables. To avoid biased estimates of β , the ‘fixed’ effect c_i in equations (1) and (2) is treated as unknown parameter to be explicitly estimated. However, inclusion of country-specific time invariant fixed effects yields consistent, but inefficient estimates—particularly if panels are small and the degree of freedom is strongly reduced such as in the small panel dataset used in this study. In contrast, in such small panels, generalized least squares random effects estimates may be more efficient, but, as discussed above, require the strong assumption of mean independence of the random effects c_i from the regressors.

Existing opportunities in B2C online commerce, such as the growing share of B2C online commerce in consumer spending, could also create incentives for technology adoption. To address this concern, despite the constraints posed by the small panel dataset from limited country-level data on B2C online sales and technology indicators, equations (1) and (2) are estimated with technology adoption measures lagged by 1 year, $Tech_{it-1}$ and $lnserver_{it-1}$. In this approach, lagged values are used since it is harder to argue that current levels of B2C internet sales affect technology adoption in

the previous year. This also captures the lagged effects of technology adoption measures on B2C online sales.

B. Variable Explanation and Data Sources

To empirically test the models in equations (1) and (2), publicly available data are taken from the Global Competitiveness Report, International Telecommunications Union, World Development Indicators, International Monetary Fund, International Labour Organization, and national sources. We also gather additional data from proprietary databases, including CEIC, Haver Analytics, and Euromonitor International. The last dataset allows B2C online commerce sales to be compared across countries and year.

Euromonitor International Retailing industry edition 2019 defines internet retailing as sales of consumer goods to the public through the internet, including those from mobile phones and tablets.² In terms of scope, it covers sales arising from pure e-commerce websites and those operated by store-based retailers. It also includes online orders for which payment is made through a store card or an online credit account on delivery or after delivery of the product. Modes of payments include postal checks, direct debit, standing orders, or other banking tools, and orders paid for cash on delivery. Click and collect orders where the payment is made in the store are excluded.

The coverage of internet retailing in this study includes a range of products from apparel and footwear, pet care products, home furnishings, to video game hardware. However, it excludes several others, such as motor vehicles, motorcycles and vehicle parts, tickets for events (e.g., sports, music concerts), travel and holiday packages, revenue generated by online gambling sites, quick delivery services of food, magazines, household goods, and DVD rentals such as Netflix, among others. Mobile internet retailing or m-commerce includes sales through mobile devices such as smartphones and tablets. These sales are also included in the internet retailing channel. Sales data are attributed to the country where the consumer, not the merchant, is based. Transactions are limited to B2C online sales and exclude consumer-to-consumer exchanges such as e-Bay. Further information on variables and data sources are presented in Table A1.1 of the Appendix.

The study covers 12 Asian economies: Azerbaijan, the People's Republic of China, India, Indonesia, Japan, Kazakhstan, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Viet Nam. The country coverage is constrained by dataset available across secondary sources. The availability of B2C online commerce data covering selected Asian countries is not the same across years. Data on internet retail sales are available starting from 2004, while those of mobile, foreign, and domestic internet retail sales are available only from 2011. Euromonitor predicted the estimated sales of each segment of B2C online commerce from 2019 to 2023. For all countries with a complete set of data on all variables used, the period covered is from 2011 to 2017 (see Table A1.2 of the Appendix for descriptive analysis for all variables).

² Based on metadata of Euromonitor International. Retailing industry edition 2019.

IV. RESULTS

In this section, the results from pooled OLS, panel random effects, and fixed effects models and their specifications with lagged technology adoption variables are described. Tables 1–6 present the summary of estimation results for the variables of interest, the technology adoption variables ($Tech_{it}$ and $server_{it}$), and financial environment readiness indicators (DC_{it} and CC_{it}). The impact of consumer spending indicators on B2C online sales will also be discussed. Full regression results are available in the online appendix.

A. Impact of Technology Adoption Variables on Business-to-Consumer Online Sales

(1) Impact of Technology Adoption Measures

Table 1 provides robust empirical evidence on the key role of internet users IUT_{it} on B2C online sales growth, particularly on internet retail sales, where IUT_{it} is statistically significant at 1%–5% levels in all models, except for the pooled OLS and lagged-adjusted specifications (models 1 and 7 of Table 1). The strong positive impact of internet users on internet retail sales is evident in its large coefficients across models, which depict the elasticity or sensitivity of B2C online sales to changes in internet access. The contribution of a 1% increase in IUT_{it} on internet retail sales growth ranges from 0.417% to 1.052%. The lagged-adjusted models also show that IUT_{it-1} has lagged positive impact on internet retail sales growth, although the coefficients are smaller than those of IUT_{it} (0.621%–1.01%). Except for model 7, IUT_{it-1} coefficients are statistically significant at 1% level across other models. The coefficient of IUT_{it-1} in model 7 is also extremely smaller than its counterparts (0.192%), suggesting the importance of controlling for time-invariant country characteristics in establishing the relationship between internet users and internet retail sales growth. Comparing the impact of IUT_{it} and IUT_{it-1} on internet retail sales shows that current internet users have a stronger effect on B2C online sales growth. While not all internet users shop online, these estimation results provide strong empirical support that the current internet population is the potential market base of internet retail sales. These results are also consistent with the findings of Ho, Kauffman, and Liang (2011).

A novel feature of this study is investigating the role of technology adoption in the subcategories of internet retail sales (i.e., MOB , DOM , and FOR). For these subcategories, controlling for time-invariant country characteristics and employing credit card penetration CC_{it} as financial readiness proxy establish the positive impact of the previous and current size of internet population on MOB , DOM , and FOR , respectively. Across all four dependent variables, IUT_{it} shows the highest impact on mobile internet retail sales with 1% increase in internet users resulting to 1.55% growth, which means that mobile shopping is highly sensitive to changes in internet access. This also provides empirical evidence on internet population as potential market base of mobile internet shopping, highlighting the crucial role of internet connectivity in m-commerce growth.

A percentage increase in IUT_{it} leads to 1.02% and 1.41% growth in FOR and DOM , respectively (models 23 and 33 of Table 1). Meanwhile, DOM manifests 1.17% growth for a percentage rise in IUT_{it} (model 36 of Table 1). In the models with MOB_{it} , DOM_{it} , and FOR_{it} as dependent variables, the coefficients of IUT_{it-1} also have smaller magnitudes than the coefficients of IUT_{it} . This illustrates the dissipating impact of the previous size of internet population on current levels of B2C online sales, strongly suggesting that the current internet population or market size is the key driver of B2C online sales growth.

Table 1: Summary of Impact of Share of Internet Users (IUT_{it}) on All Categories of Business-to-Consumer Online Sales

Financial Variable Proxy	Technology Adoption Variables: $\ln IUT_{it}$ and $\ln server_{it}$						Lagged Technology Adoption Variables: $\ln IUT_{it-1}$ and $\ln server_{it-1}$			
	Credit Card Penetration: $\ln CC_{it}$			Debit Card Penetration: $\ln DC_{it}$			Credit Card Penetration: $\ln CC_{it}$		Debit Card Penetration: $\ln DC_{it}$	
	Pooled OLS	RE	FE	Pooled OLS	RE	FE	RE	FE	RE	FE
Dependent variable: $\ln(\text{internet retail sales}) (\ln IRS_{it})$										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln IUT_{it}$ ($\ln IUT_{it-1}$)	-0.651 (0.472)	0.793*** (0.160)	1.052*** (0.196)	-2.197** (0.785)	0.417** (0.211)	1.023*** (0.288)	0.192 (0.500)	0.966*** (0.171)	0.621*** (0.183)	1.009*** (0.304)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.678*** (0.164)	0.148*** (0.0557)	0.0313 (0.0583)	0.559*** (0.148)	0.145** (0.0734)	0.00449 (0.0655)	0.416*** (0.128)	0.121** (0.0480)	0.146* (0.0763)	0.0205 (0.0718)
Financial variable proxy	0.311* (0.151)	0.232* (0.120)	0.339*** (0.109)	1.722*** (0.516)	0.669* (0.374)	0.455** (0.205)	0.287** (0.137)	0.172 (0.108)	0.637* (0.337)	0.609*** (0.220)
Dependent variable: $\ln(\text{mobile internet retail sales}) (\ln MOB_{it})$										
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
$\ln IUT_{it}$ ($\ln IUT_{it-1}$)	-0.453 (0.551)	-0.453 (0.551)	1.548** (0.785)	-2.391** (1.045)	-0.0523 (1.374)	1.437 (1.837)	-0.396 (0.525)	1.057* (0.546)	-0.774 (0.949)	0.384 (1.151)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.930*** (0.135)	0.930*** (0.135)	0.376*** (0.121)	0.776*** (0.113)	0.485*** (0.0888)	0.279 (0.172)	1.192*** (0.165)	0.514*** (0.106)	0.766*** (0.128)	0.502** (0.231)
Financial variable proxy	0.435 (0.299)	0.435 (0.299)	1.448*** (0.328)	2.816** (1.228)	3.059** (1.280)	2.339* (1.214)	0.146 (0.272)	1.491*** (0.351)	2.866** (1.227)	2.732** (1.291)
Dependent variable: $\ln(\text{foreign internet retail sales}) (\ln FOR_{it})$										
	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
$\ln IUT_{it}$ ($\ln IUT_{it-1}$)	0.636 (0.543)	0.636 (0.543)	1.020** (0.463)	-0.365 (0.546)	-0.365 (0.546)	0.666 (0.409)	0.619 (0.377)	0.937*** (0.0811)	-0.342 (0.480)	0.519 (0.424)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.423*** (0.138)	0.423*** (0.138)	0.148* (0.0797)	0.374** (0.159)	0.374** (0.159)	0.0702 (0.103)	0.583*** (0.169)	0.207*** (0.0482)	0.497*** (0.164)	0.166 (0.133)
Financial variable proxy	0.423** (0.197)	0.423** (0.197)	0.0180 (0.173)	1.607*** (0.458)	1.607*** (0.458)	1.168** (0.583)	0.220 (0.200)	0.0305 (0.163)	1.458*** (0.471)	0.947 (0.739)
Dependent variable: $\ln(\text{domestic internet retail sales}) (\ln DOM_{it})$										
	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
$\ln IUT_{it}$ ($\ln IUT_{it-1}$)	-1.061 (0.679)	-1.061 (0.679)	1.407*** (0.308)	-2.792*** (0.849)	0.415 (0.497)	1.170** (0.456)	-0.984* (0.552)	0.992*** (0.188)	-0.0328 (0.452)	0.593 (0.377)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.719*** (0.176)	0.719*** (0.176)	0.0412 (0.0522)	0.569*** (0.175)	0.0908 (0.0679)	0.00332 (0.0576)	0.955*** (0.220)	0.107** (0.0527)	0.192** (0.0933)	0.104 (0.0884)
Financial variable proxy	0.502 (0.307)	0.502 (0.307)	0.113 (0.123)	2.706** (0.882)	1.694*** (0.655)	0.908* (0.490)	0.245 (0.285)	0.235** (0.111)	1.936** (0.796)	1.094* (0.654)

OLS = ordinary least squares, FE = fixed effects, RE = random effects.

Notes: Figures in parenthesis are robust standard errors. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Source: Author's estimation.

When the mode of internet access is limited to high-speed internet connectivity or fixed broadband internet subscription, $FBIS_{it}$ and $FBIS_{it-1}$, the importance of fast internet connection in m-commerce becomes more evident (Table 2). A 1% increase in $FBIS_{it}$ per 100 population contributes 0.385% growth in m-commerce retail sales in a fixed effects model controlled for CC_{it} (model 13 of Table 2) while contributing 0.493% in foreign internet retail sales growth in pooled OLS and random effects models (model 21 and 22 of Table 2).

$FBIS_{it-1}$ coefficients in fixed effects models employing CC_{it} and DC_{it} have positive coefficients of 0.685% and 0.719%, respectively (models 18 and 20 of Table 2). The impact of $FBIS_{it-1}$ on other segments of B2C online sales are lower, ranging from 0.164% to 0.234%, suggesting less elastic response to changes in past levels of fixed broadband internet connectivity. Overall, $FBIS_{it-1}$ coefficients are larger than the coefficients of the current population of fixed broadband subscriptions $FBIS_{it}$, suggesting that high-speed internet connectivity has persistent effects on B2C online sales. This further implies that earlier adoption of advanced technologies such as high-speed internet connectivity stimulates faster B2C online sales growth. Meanwhile, the results in Table 3 provide no empirical support on the direct impact of IIB_{it} on B2C online sales. Hence, while internet access and speed stimulate B2C online sales growth, the same cannot be said on international internet bandwidth or the capacity of international connections between countries to transmit internet traffic.

The findings in Table 4 confirm the importance of MBS_{it} in m-commerce, or the active mobile broadband subscriptions per 100 population MBS_{it} and MBS_{it-1} have positive and statistically significant impact on mobile shopping for all models where debit card penetration DC_{it} is used as financial readiness proxy, contributing 0.352%–0.783% in m-commerce sales growth for every 1% increase in mobile broadband subscription per 100 people (models 15–16 and 19–20). Meanwhile, in a fixed effects model using CC_{it} as financial readiness indicator, a percentage rise in MBS_{it-1} contributes 0.8% growth in m-commerce (model 18). For other segments of B2C online sales (*i. e.* IRS_{it} , DOM_{it} , and FOR_{it}), the difference in coefficients, signs, and statistical significance of MBS_{it} and MBS_{it-1} in the contemporaneous and lagged-variable fixed effects models indicate potential endogeneity bias in the specifications of the contemporaneous models. To illustrate, while the coefficient of MBS_{it} is –0.00955 in the fixed effects model (model 3 of Table 4), it changes to 0.343 and becomes statistically significant in the lagged-adjusted fixed effects model (model 3 of Table 5).

The results in Table 5 show that B2C online sales are highly elastic or responsive to changes in mobile telephone subscription (MTS_{it} and MTS_{it-1}). While all B2C segments show a higher degree of responsiveness to changes in MTS_{it} and MTS_{it-1} , m-commerce sales emerge as the most sensitive to this technology adoption measure. To illustrate, mobile telephone subscription coefficients (3.445%–5.563%) are positive and statistically significant in all fixed effects models, both contemporaneous and lagged-adjusted (models 13, 16, 18, and 20 of Table 5). In contrast, coefficients of other B2C online sales segments range from 1.027% to 2.4%. The high elasticity of m-commerce for mobile phone subscriptions highlights the growing importance in B2C online sales of relatively cheaper and easy-to-use high-mobility devices such as mobile phones compared to more sophisticated and low-mobility hardware (e.g., personal computers and laptops). Mobile telephone subscriptions are also indicative of the population size of mobile phone ownership. Since a mobile phone is one of the devices that can be used to access m-commerce, mobile phone subscription along with internet population represent the indicators for the demand side of the m-commerce market.

The declining relevance of fixed telephone lines, FTL_{it} and FTL_{it-1} , in B2C online sales are evident in Table 6. Where FTL_{it-1} is statistically significant, the coefficients are negative (models 8, 18, 24, 25, 28, 29, and 38 of Table 6). While m-commerce is highly responsive to changes in past levels of mobile telephone subscriptions MTS_{it-1} and shows positive coefficients, model 18 of Table 6 shows

Table 2: Summary of Impact of Fixed Broadband Internet Subscription per 100 Population ($FBIS_{it}$) on All Categories of Business-to-Consumer Online Sale

Financial Variable Proxy	Technology Adoption Variables: $lnIUT_{it}$ and $lnserver_{it}$						Lagged Technology Adoption Variables: $lnIUT_{it-1}$ and $lnserver_{it-1}$			
	Credit Card Penetration: $lnCC_{it}$			Debit Card Penetration: $lnDC_{it}$			Credit Card Penetration: $lnCC_{it}$		Debit Card Penetration: $lnDC_{it}$	
	Pooled OLS	RE	FE	Pooled OLS	RE	FE	RE	FE	RE	FE
Dependent variable: ln(internet retail sales) ($lnIRS_{it}$)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$lnFBIS_{it}$ ($lnFBIS_{it-1}$)	-0.119 (0.209)	0.0319 (0.0858)	0.0819 (0.0950)	-0.680 (0.391)	-0.121 (0.141)	0.0632 (0.182)	0.0917 (0.125)	0.171** (0.0867)	0.0171 (0.115)	0.122 (0.150)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.678*** (0.173)	0.264*** (0.0741)	0.119** (0.0529)	0.576*** (0.166)	0.185** (0.0799)	0.0702 (0.0735)	0.314*** (0.0702)	0.227*** (0.0724)	0.178** (0.0759)	0.0634 (0.0714)
Financial variable proxy	0.226 (0.145)	0.318*** (0.101)	0.513*** (0.112)	1.151* (0.607)	1.010** (0.393)	0.809** (0.398)	0.238*** (0.0850)	0.123 (0.171)	0.832** (0.347)	0.721** (0.312)
Dependent variable: ln(mobile internet retail sales) ($lnMOB_{it}$)										
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
$lnFBIS_{it}$ ($lnFBIS_{it-1}$)	-0.278 (0.245)	-0.278 (0.245)	0.385** (0.192)	-1.285 (0.861)	-1.285 (0.861)	0.538 (0.421)	-0.247 (0.277)	0.685*** (0.125)	-1.262* (0.747)	0.719*** (0.161)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.905*** (0.133)	0.905*** (0.133)	0.478*** (0.0949)	0.682*** (0.189)	0.682*** (0.189)	0.353** (0.174)	1.164*** (0.171)	0.604*** (0.131)	0.848*** (0.225)	0.485** (0.241)
Financial variable proxy	0.493 (0.358)	0.493 (0.358)	1.753*** (0.260)	2.923* (1.596)	2.923* (1.596)	2.810*** (0.658)	0.166 (0.316)	1.590*** (0.357)	2.518 (1.583)	2.886*** (0.814)
Dependent variable: ln(foreign internet retail sales) ($lnFOR_{it}$)										
	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
$lnFBIS_{it}$ ($lnFBIS_{it-1}$)	0.493* (0.277)	0.493* (0.277)	0.00889 (0.0718)	-0.0281 (0.337)	-0.0281 (0.337)	0.101 (0.254)	0.375 (0.248)	0.158 (0.109)	-0.00245 (0.212)	0.199 (0.162)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.467*** (0.132)	0.467*** (0.132)	0.236*** (0.0451)	0.384** (0.153)	0.384** (0.153)	0.111 (0.121)	0.607*** (0.153)	0.310*** (0.0555)	0.517*** (0.162)	0.166 (0.140)
Financial variable proxy	0.293 (0.201)	0.293 (0.201)	0.242** (0.0973)	1.459** (0.568)	1.459** (0.568)	1.580*** (0.399)	0.163 (0.163)	-0.0101 (0.132)	1.265*** (0.444)	1.431*** (0.462)
Dependent variable: ln(domestic internet retail sales) ($lnDOM_{it}$)										
	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
$lnFBIS_{it}$ ($lnFBIS_{it-1}$)	-0.418 (0.396)	-0.418 (0.396)	0.0685 (0.0782)	-1.101 (0.609)	-0.643 (0.460)	0.0902 (0.195)	-0.414* (0.251)	0.164** (0.0800)	-0.00510 (0.143)	0.234** (0.0935)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.683*** (0.179)	0.683*** (0.179)	0.158** (0.0637)	0.530** (0.216)	0.384** (0.159)	0.0806 (0.0902)	0.935*** (0.230)	0.215*** (0.0829)	0.309** (0.121)	0.103 (0.112)
Financial variable proxy	0.542 (0.388)	0.542 (0.388)	0.396*** (0.146)	2.428* (1.200)	2.494*** (0.960)	1.745*** (0.264)	0.253 (0.308)	0.195 (0.227)	2.064*** (0.758)	1.646*** (0.356)

OLS = ordinary least squares, FE = fixed effects, RE = random effects.

Notes: Figures in parenthesis are robust standard errors. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Source: Author's estimation.

Table 3: Summary of Impact of International Internet Bandwidth (kb/s) per Internet User (IIB_{it}) on All Categories of Business-to-Consumer Online Sales

Financial Variable Proxy	Technology Adoption Variables: $lnIIB_{it}$ and $lnserver_{it}$						Lagged Technology Adoption Variables: $lnIIB_{it-1}$ and $lnserver_{it-1}$			
	Credit Card Penetration: $lnCC_{it}$			Debit Card Penetration: $lnDC_{it}$			Credit Card Penetration: $lnCC_{it}$		Debit Card Penetration: $lnDC_{it}$	
	Pooled OLS	RE	FE	Pooled OLS	RE	FE	RE	FE	RE	FE
Dependent variable: ln(internet retail sales) ($lnIRS_{it}$)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$lnIIB_{it}$ ($lnIIB_{it-1}$)	-0.397* (0.216)	-0.0221 (0.0638)	-0.0240 (0.0539)	-0.709** (0.243)	-0.144 (0.126)	-0.0206 (0.105)	-0.0794 (0.0836)	-0.00346 (0.0721)	-0.0899 (0.0950)	0.0293 (0.0807)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.742*** (0.196)	0.248*** (0.0807)	0.130** (0.0571)	0.754*** (0.175)	0.281** (0.120)	0.0805 (0.0951)	0.373*** (0.109)	0.232*** (0.0878)	0.232** (0.101)	0.0583 (0.0888)
Financial variable proxy	0.147 (0.164)	0.342*** (0.112)	0.571*** (0.0924)	0.327 (0.368)	0.851*** (0.328)	0.906*** (0.284)	0.277*** (0.0645)	0.284** (0.134)	0.850** (0.334)	0.901*** (0.290)
Dependent variable: ln(mobile internet retail sales) ($lnMOB_{it}$)										
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
$lnIIB_{it}$ ($lnIIB_{it-1}$)	-0.348 (0.232)	-0.348 (0.232)	0.0945 (0.175)	-0.799* (0.372)	0.0291 (0.302)	0.165 (0.295)	-0.289** (0.122)	0.146 (0.167)	-0.0540 (0.221)	0.156 (0.177)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.956*** (0.142)	0.956*** (0.142)	0.492*** (0.0962)	0.963*** (0.143)	0.489*** (0.115)	0.315* (0.171)	1.227*** (0.165)	0.545*** (0.0953)	0.732*** (0.144)	0.411* (0.220)
Financial variable proxy	0.413 (0.290)	0.413 (0.290)	1.744*** (0.391)	1.355 (0.911)	2.999*** (0.860)	3.568*** (0.868)	0.0764 (0.248)	1.689*** (0.357)	2.518*** (0.753)	3.250*** (0.827)
Dependent variable: ln(foreign internet retail sales) ($lnFOR_{it}$)										
	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
$lnIIB_{it}$ ($lnIIB_{it-1}$)	-0.0728 (0.192)	-0.0728 (0.192)	-0.0417 (0.0607)	-0.173 (0.205)	-0.127 (0.154)	-0.0481 (0.0803)	0.104 (0.212)	0.000719 (0.0999)	-0.105 (0.139)	-0.0550 (0.117)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.428*** (0.159)	0.428*** (0.159)	0.243*** (0.0444)	0.409* (0.188)	0.370** (0.166)	0.135 (0.122)	0.557*** (0.183)	0.313*** (0.0862)	0.498** (0.194)	0.239 (0.190)
Financial variable proxy	0.520*** (0.197)	0.520*** (0.197)	0.295*** (0.113)	1.362** (0.472)	1.543*** (0.393)	1.695*** (0.516)	0.327* (0.188)	0.138 (0.122)	1.378*** (0.396)	1.446*** (0.426)
Dependent variable: ln(domestic internet retail sales) ($lnDOM_{it}$)										
	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
$lnIIB_{it}$ ($lnIIB_{it-1}$)	-0.602** (0.242)	-0.602** (0.242)	0.0144 (0.0621)	-0.829** (0.286)	-0.0337 (0.0935)	0.0550 (0.0762)	-0.532*** (0.165)	0.00311 (0.0706)	-0.164 (0.101)	0.0113 (0.0712)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.776*** (0.194)	0.776*** (0.194)	0.160*** (0.0587)	0.779*** (0.201)	0.180** (0.0838)	0.0653 (0.0871)	1.045*** (0.247)	0.216** (0.0966)	0.381*** (0.141)	0.133 (0.136)
Financial variable proxy	0.457 (0.304)	0.457 (0.304)	0.411** (0.174)	1.038 (0.827)	2.157*** (0.611)	1.884*** (0.342)	0.102 (0.279)	0.349** (0.175)	1.927*** (0.650)	1.720*** (0.339)

OLS = ordinary least squares, FE = fixed effects, RE = random effects.

Notes: Figures in parenthesis are robust standard errors. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Source: Author's estimation.

Table 4: Summary of Impact of Mobile Broadband Subscriptions per 100 Population (MBS_{it}) on All Categories of Business-to-Consumer Online Sales

Financial Variable Proxy	Technology Adoption Variables: $\ln MBS_{it}$ and $\ln server_{it}$						Lagged Technology Adoption Variables: $\ln MBS_{it-1}$ and $\ln server_{it-1}$			
	Credit Card Penetration: $\ln CC_{it}$			Debit Card Penetration: $\ln DC_{it}$			Credit Card Penetration: $\ln CC_{it}$		Debit Card Penetration: $\ln DC_{it}$	
	Pooled OLS	RE	FE	Pooled OLS	RE	FE	RE	FE	RE	FE
Dependent variable: $\ln(\text{internet retail sales}) (\ln IRS_{it})$										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln MBS_{it}$ ($\ln MBS_{it-1}$)	-0.0829 (0.243)	0.0271 (0.115)	-0.00955 (0.137)	-0.204 (0.205)	-0.0608 (0.0404)	-0.0488 (0.0701)	0.242** (0.114)	0.343*** (0.119)	-0.0314 (0.0678)	0.0998 (0.0934)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.686*** (0.163)	0.281*** (0.0802)	0.121** (0.0502)	0.677*** (0.145)	0.177** (0.0813)	0.0727 (0.0776)	0.280*** (0.0560)	0.159*** (0.0554)	0.162** (0.0784)	0.0408 (0.0597)
Financial variable proxy	0.157 (0.180)	0.331*** (0.110)	0.562*** (0.0948)	0.586 (0.404)	0.945*** (0.327)	1.015*** (0.309)	0.270*** (0.0583)	0.391*** (0.125)	0.873*** (0.319)	0.759** (0.295)
Dependent variable: $\ln(\text{mobile internet retail sales}) (\ln MOB_{it})$										
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
$\ln MBS_{it}$ ($\ln MBS_{it-1}$)	0.0240 (0.248)	0.0240 (0.248)	0.278 (0.193)	-0.0874 (0.300)	0.363** (0.144)	0.352* (0.185)	-0.0411 (0.170)	0.800*** (0.144)	0.607*** (0.172)	0.783*** (0.0996)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.932*** (0.154)	0.932*** (0.154)	0.536*** (0.113)	0.911*** (0.166)	0.419*** (0.115)	0.367* (0.191)	1.206*** (0.173)	0.529*** (0.113)	0.512*** (0.172)	0.434* (0.232)
Financial variable proxy	0.413 (0.382)	0.413 (0.382)	1.751*** (0.250)	1.632 (0.993)	3.357*** (0.720)	3.650*** (0.754)	0.108 (0.368)	1.804*** (0.349)	2.942*** (0.679)	2.936*** (0.698)
Dependent variable: $\ln(\text{foreign internet retail sales}) (\ln FOR_{it})$										
	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
$\ln MBS_{it}$ ($\ln MBS_{it-1}$)	-0.0563 (0.173)	-0.0563 (0.173)	0.0319 (0.108)	-0.197 (0.165)	0.0723 (0.0943)	0.0496 (0.0979)	-0.0913 (0.112)	0.244** (0.114)	0.0663 (0.111)	0.233* (0.139)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.426*** (0.139)	0.426*** (0.139)	0.243*** (0.0493)	0.397** (0.147)	0.271** (0.122)	0.122 (0.113)	0.577*** (0.162)	0.278*** (0.0617)	0.264** (0.125)	0.180 (0.136)
Financial variable proxy	0.485** (0.216)	0.485** (0.216)	0.245* (0.145)	1.453*** (0.407)	1.774*** (0.352)	1.709*** (0.551)	0.317 (0.219)	0.203 (0.169)	1.679*** (0.426)	1.275*** (0.373)
Dependent variable: $\ln(\text{domestic internet retail sales}) (\ln DOM_{it})$										
	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
$\ln MBS_{it}$ ($\ln MBS_{it-1}$)	-0.141 (0.312)	-0.141 (0.312)	0.0325 (0.146)	-0.301 (0.364)	0.0815 (0.0855)	0.0785 (0.107)	-0.0667 (0.181)	0.376*** (0.104)	0.275*** (0.0910)	0.303*** (0.0910)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.734*** (0.189)	0.734*** (0.189)	0.168** (0.0691)	0.695*** (0.175)	0.109 (0.0680)	0.0872 (0.0854)	0.968*** (0.223)	0.135** (0.0571)	0.126 (0.0831)	0.106 (0.0964)
Financial variable proxy	0.285 (0.370)	0.285 (0.370)	0.418** (0.164)	1.392 (0.909)	1.975*** (0.397)	1.881*** (0.401)	-0.0109 (0.360)	0.470*** (0.140)	1.580*** (0.311)	1.493*** (0.368)

OLS = ordinary least squares, FE = fixed effects, RE = random effects.

Notes: Figures in parenthesis are robust standard errors. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Source: Author's estimation.

Table 5: Summary of Impact of Mobile Telephone Subscriptions per 100 Population (MTS_{it}) on All Categories of Business-to-Consumer Online Sale

Financial Variable Proxy	Technology Adoption Variables: $\ln MTS_{it}$ and $\ln server_{it}$						Lagged Technology Adoption Variables: $\ln MTS_{it-1}$ and $\ln server_{it-1}$			
	Credit Card Penetration: $\ln CC_{it}$			Debit Card Penetration: $\ln DC_{it}$			Credit Card Penetration: $\ln CC_{it}$		Debit Card Penetration: $\ln DC_{it}$	
	Pooled OLS	RE	FE	Pooled OLS	RE	FE	RE	FE	RE	FE
Dependent variable: $\ln(\text{internet retail sales}) (\ln IRS_{it})$										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln MTS_{it}$ ($\ln MTS_{it-1}$)	-1.310 (1.597)	-1.310 (1.597)	1.647*** (0.567)	-3.366*** (0.696)	-0.0387 (0.435)	0.596 (0.654)	-1.410 (1.303)	0.806* (0.412)	0.717 (0.501)	1.027* (0.572)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.703*** (0.161)	0.703*** (0.161)	0.0710* (0.0421)	0.748*** (0.144)	0.179** (0.0827)	0.0465 (0.0572)	0.917*** (0.184)	0.148** (0.0686)	0.131* (0.0788)	0.0236 (0.0735)
Financial variable proxy	0.243 (0.155)	0.243 (0.155)	0.345*** (0.121)	1.376*** (0.214)	0.859** (0.404)	0.504 (0.377)	0.326 (0.279)	0.225 (0.204)	0.651* (0.363)	0.570*** (0.212)
Dependent variable: $\ln(\text{mobile internet retail sales}) (\ln MOB_{it})$										
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
$\ln MTS_{it}$ ($\ln MTS_{it-1}$)	1.029 (2.261)	1.029 (2.261)	5.563*** (1.235)	-4.592*** (1.050)	-4.592*** (1.050)	6.944*** (1.301)	-0.0495 (1.182)	2.540** (2.261)	-3.201*** (0.859)	3.445** (1.634)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.888*** (0.147)	0.888*** (0.147)	0.391*** (0.0622)	1.042*** (0.163)	1.042*** (0.163)	0.236** (0.104)	1.194*** (0.176)	0.460*** (0.125)	1.354*** (0.213)	0.309 (0.195)
Financial variable proxy	0.139 (0.535)	0.139 (0.535)	0.681** (0.317)	1.638* (0.861)	1.638* (0.861)	1.380*** (0.501)	0.0245 (0.430)	1.037*** (0.351)	1.118 (0.824)	1.755** (0.889)
Dependent variable: $\ln(\text{foreign internet retail sales}) (\ln FOR_{it})$										
	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
$\ln MTS_{it}$ ($\ln MTS_{it-1}$)	3.029 (2.033)	3.029 (2.033)	0.430 (0.328)	-1.459* (0.815)	-1.459* (0.815)	1.940* (1.041)	0.845 (1.410)	0.430 (0.328)	-0.989* (0.574)	0.640 (0.664)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.322* (0.166)	0.322* (0.166)	0.280*** (0.0733)	0.399** (0.163)	0.399** (0.163)	0.0741 (0.110)	0.526*** (0.192)	0.280*** (0.0733)	0.538*** (0.204)	0.163 (0.144)
Financial variable proxy	0.165 (0.256)	0.165 (0.256)	0.106 (0.210)	1.520*** (0.416)	1.520*** (0.416)	0.978** (0.397)	0.235 (0.249)	0.106 (0.210)	1.293*** (0.453)	1.099*** (0.396)
Dependent variable: $\ln(\text{domestic internet retail sales}) (\ln DOM_{it})$										
	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
$\ln MTS_{it}$ ($\ln MTS_{it-1}$)	-3.523 (2.697)	-3.523 (2.697)	2.400*** (0.492)	-5.676*** (1.147)	-5.676*** (1.147)	2.218*** (0.577)	-2.677* (1.499)	1.077** (0.473)	-4.386*** (0.853)	1.083* (0.651)
$\ln server_{it}$ ($\ln server_{it-1}$)	0.814*** (0.179)	0.814*** (0.179)	0.0728* (0.0442)	0.840*** (0.164)	0.840*** (0.164)	0.0337 (0.0540)	1.079*** (0.225)	0.108* (0.0637)	1.132*** (0.202)	0.0667 (0.0879)
Financial variable proxy	0.428 (0.551)	0.428 (0.551)	0.216** (0.104)	1.361** (0.683)	1.361** (0.683)	1.055** (0.432)	0.0836 (0.402)	0.259 (0.196)	0.833 (0.559)	1.149** (0.514)

OLS = ordinary least squares, FE = fixed effects, RE = random effects.

Notes: Figures in parenthesis are robust standard errors. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Source: Author's estimation.

Table 6: Summary of Impact of Fixed Telephone Lines per 100 Population ($F_{TL_{it}}$) on All Categories of Business-to-Consumer Online Sale

Financial Variable Proxy	Technology Adoption Variables $lnF_{TL_{it}}$ and $lnserver_{it}$						Lagged Technology Adoption Variables: $lnF_{TL_{it-1}}$ and $lnserver_{it-1}$			
	Credit Card Penetration: $lnCC_{it}$			Debit Card Penetration: $lnDC_{it}$			Credit Card Penetration: $lnCC_{it}$		Debit Card Penetration: $lnDC_{it}$	
	Pooled OLS	RE	FE	Pooled OLS	RE	FE	RE	FE	RE	FE
Dependent variable: ln(internet retail sales) ($lnIRS_{it}$)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$lnF_{TL_{it}}$ ($lnF_{TL_{it-1}}$)	0.281 (0.565)	0.281 (0.565)	-0.349 (0.345)	-0.365 (0.559)	-0.266 (0.270)	0.0551 (0.328)	0.193 (0.557)	-0.645** (0.278)	-0.326 (0.379)	-0.343 (0.306)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.682*** (0.150)	0.682*** (0.150)	0.0867** (0.0392)	0.610*** (0.145)	0.270*** (0.102)	0.0599 (0.0625)	0.869*** (0.191)	0.149* (0.0813)	0.306*** (0.113)	0.0480 (0.0680)
Financial variable proxy	0.0749 (0.224)	0.0749 (0.224)	0.534*** (0.0864)	0.663 (0.517)	1.027*** (0.388)	0.898*** (0.295)	0.0441 (0.200)	0.437*** (0.144)	1.062** (0.442)	0.775** (0.312)
Dependent variable: ln(mobile internet retail sales) ($lnMOB_{it}$)										
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
$lnF_{TL_{it}}$ ($lnF_{TL_{it-1}}$)	-0.109 (0.833)	-0.109 (0.833)	-0.991 (0.908)	-1.304 (0.939)	-1.304 (0.939)	0.0845 (1.183)	-0.296 (0.870)	-1.542* (0.816)	-1.350 (0.825)	-0.817 (1.005)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.914*** (0.132)	0.914*** (0.132)	0.428*** (0.136)	0.722*** (0.153)	0.722*** (0.153)	0.389** (0.160)	1.188*** (0.158)	0.503*** (0.144)	1.064*** (0.143)	0.475* (0.260)
Financial variable proxy	0.308 (0.691)	0.308 (0.691)	1.976*** (0.208)	2.611* (1.376)	2.611* (1.376)	3.736*** (1.151)	0.239 (0.611)	1.833*** (0.504)	2.232* (1.257)	3.001*** (1.109)
Dependent variable: ln(foreign internet retail sales) ($lnFOR_{it}$)										
	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
$lnF_{TL_{it}}$ ($lnF_{TL_{it-1}}$)	-0.386 (0.342)	-0.386 (0.342)	-0.509 (0.372)	-0.900*** (0.308)	-0.900*** (0.308)	0.375 (0.429)	-0.443 (0.331)	-0.466* (0.268)	-0.946*** (0.232)	0.160 (0.531)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.381** (0.163)	0.381** (0.163)	0.179** (0.0722)	0.224* (0.131)	0.224* (0.131)	0.150 (0.103)	0.543*** (0.178)	0.269*** (0.0774)	0.385** (0.159)	0.217* (0.131)
Financial variable proxy	0.670** (0.310)	0.670** (0.310)	0.340** (0.132)	2.188*** (0.357)	2.188*** (0.357)	1.798*** (0.565)	0.574* (0.316)	0.237 (0.171)	2.025*** (0.272)	1.458*** (0.505)
Dependent variable: ln(domestic internet retail sales) ($lnDOM_{it}$)										
	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
$lnF_{TL_{it}}$ ($lnF_{TL_{it-1}}$)	0.426 (0.801)	0.426 (0.801)	-0.396 (0.389)	-0.795 (0.906)	-0.795 (0.906)	0.229 (0.342)	0.489 (0.733)	-0.735** (0.291)	-0.741 (0.769)	-0.125 (0.429)
$lnserver_{it}$ ($lnserver_{it-1}$)	0.744*** (0.176)	0.744*** (0.176)	0.0961 (0.0746)	0.555*** (0.165)	0.555*** (0.165)	0.104* (0.0629)	0.981*** (0.216)	0.121 (0.0832)	0.848*** (0.154)	0.136 (0.103)
Financial variable proxy	-0.144 (0.620)	-0.144 (0.620)	0.535*** (0.163)	1.971 (1.259)	1.971 (1.259)	1.905*** (0.428)	-0.381 (0.516)	0.524*** (0.164)	1.565 (1.125)	1.596*** (0.450)

OLS = ordinary least squares, FE = fixed effects, RE = random effects.

Notes: Figures in parenthesis are robust standard errors. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Source: Author's estimation.

that it is also sensitive to changes in FTL_{it-1} but has a negative coefficient (-1.542). Moreover, models 24 and 25 of Table 6 show that a contemporaneous level of fixed telephone lines FTL_{it} has a negative and statistically significant impact on foreign retail sales, a fast-growing segment of B2C online sales. The impact of FTL_{it} on other segments of B2C online sales is either positive or negative but not statistically significant. The overall empirical evidence means that while fixed telephone lines have served as the precursor for the upgrading to high-speed wired broadband (e.g., asymmetric digital subscriber line, cable modem, and on to fiber optics) this traditional mode of telecommunications does not support B2C online sales growth and is even detrimental to m-commerce and foreign internet retail sales, two segments of B2C online sales with high-growth prospects.

The similarity in the results between pooled OLS and random effects is due to the lack of variation in the small sample size. The negative and sometimes statistically significant coefficients of technology adoption measures observed in pooled OLS and random effects models reflect the recommendations in econometric literature that the fixed effects model is to be preferred over the pooled OLS and random effects models. The results show that not explicitly estimating time-invariant unobservable country heterogeneity appears to bias coefficient estimates and significance levels. The stark difference between estimates in the models for the fixed effects, pooled OLS, and random effects supports the interpretation that technology adoption measures and control variables are correlated with unobservable country characteristics such as geography, culture, institutions, and history of technology development or path dependence.

(2) Impact of Secure Internet Server Penetration as Proxy for the Supply Side of Business-to-Consumer Online Sales

M-commerce sales are highly responsive to changes in secure internet server penetration ($server_{it}$ and $server_{it-1}$), which has elastic coefficients ranging from 1.164% to 1.354% across different models. The coefficients of both contemporaneous and lagged numbers of secure internet servers are positive and statistically significant in m-commerce models that use the following technology adoption variables as proxy for B2C online sales market size: $FBIS$, IIB , MBS , and FTL (models 11–20 of Tables 2, 3, 4, and 6).

The positive and statistically significant relationship between secure internet server penetration and other segments of B2C online sales are also evident in other models, particularly when credit card penetration is used as financial readiness proxy. These results underscore the importance of protecting sensitive information such as credit card details in online shopping, especially mobile shopping. Moreover, the coefficients of $server_{it-1}$ have larger magnitudes than those of $server_{it}$ in all models. This suggests that earlier adoption of secure internet servers stimulates higher B2C online sales growth.

The robustness of $server_{it}$ and $server_{it-1}$ across different estimation specifications provides empirical support that secure internet server penetration is the indicator that represents the supply side of the market for all segments of B2C online sales. Lastly, these results support findings from previous studies on the link between internet security and B2C online commerce (Ho, Kauffman, and Liang 2011; Burroughs and Sabherwal 2002; Chau and Deng 2018; Lee and Wong 2016; Alyoubi 2015; Sarkar, Chauhan, and Khare 2020; Zhu, Mou, and Benyoucef 2019).

B. The Impact of Financial Environment Readiness Indicators on Business-to-Consumer Online Sales

Debit card penetration DC_{it} has positive and statistically significant coefficients in all models of all segments of B2C online sales (i.e., *IRS*, *MOB*, *DOM*, and *FOR*) when technology adoption indicators *IIB* and *MBS* are used as proxies for B2C online market size (debit card penetration DC_{it} columns of Tables 3 and 4). M-commerce emerges as the most responsive segment of B2C online sales to changes in DC_{it} , which has statistically significant and highly elastic coefficients ranging from 1.380% to 3.736% across different specifications (models 11–20 of Tables 1–6).

Domestic internet retail sales are also sensitive to variations in debit card penetration DC_{it} with various estimation results yielding statistically significant coefficients from 1.055% to 2.494% (models 34–36 and 39–40 of Tables 1–6). Meanwhile, foreign internet retail sales exhibit the same behavior but with smaller range of coefficients (1.168%–2.188%) as seen in models 21–30 of Tables 2–6. In general, models 4–6 and 9–10 of Tables 2–6 show that internet retail sales are inelastic to changes in debit card penetration DC_{it} (0.277%–0.906%) but evidence of elasticity is also apparent when controlled for *MBS*, FTL_{it} , and FTL_{it-1} (1.01%–1.092%).

Empirical evidence points to m-commerce as being highly sensitive to changes in credit card penetration CC_{it} with coefficients ranging from 1.037% to 1.971% seen in different estimation results (models 11–20 of Tables 1–6). Except for pooled OLS estimations, the coefficients of credit card penetration CC_{it} are positive and statistically significant in all internet retail sales models controlled for *IIB* and *MBS*, respectively (models 2–10 of Tables 3 and 4). However, all these coefficients are inelastic (0.270%–0.571%). While several models establish direct impacts of credit card penetration CC_{it} on foreign internet retail sales and domestic internet retail sales, respectively, these relationships are all inelastic (models 21–40 of Tables 1–6).

Overall, these results complement the earlier findings of UNCTAD (2017) that bank accounts have a more significant influence than credit cards on B2C online sales payment readiness. Debit cards are usually issued upon opening a bank account, which is not normally the case with credit cards. Hence, the importance of bank accounts in B2C online sales, particularly in m-commerce, explains the robust results of debit card penetration DC_{it} compared to credit card penetration CC_{it} . Ho, Kauffman, and Liang (2011) fail to establish an empirical evidence on the relationship between B2C online sales and financial cards penetration. The findings of this study fill a crucial gap in empirical literature on the impact of financial environment readiness on B2C online sales.

C. Impact of Socioeconomic Consumer Spending Indicators on Business-to-Consumer Online Sales³

The set of control variables on socioeconomic indicators of consumer spending impact on B2C online sales differently, depending on the model specifications used. Estimation results show evidence that inflation inf_{it} negatively impacts B2C online commerce (from –0.225% to –0.113%) in different modifications of fixed effects model. The difference in magnitude and sign of coefficients of inf_{it} between fixed effects and random effects models can be attributed to the omitted variable bias that results from unobservable country heterogeneity not being controlled.

³ Full regression results supporting the discussions in this section and those in Tables 1–6 are available in the online appendix at <https://www.adb.org/publications/technology-adoption-b2c-e-commerce-asia>.

Estimation results yield mixed evidence about the impact of the employment rate on B2C online sales. Several models show negative impact, while others present a positive relationship. M-commerce appears to be most responsive to changes in employment rate with coefficients ranging from -19.48% to -5.13% in different model specifications. This suggests that improving employment conditions, and therefore consumer confidence (Belessiotis 1996), cause shifts in the shopping behavior of consumers, motivating them to explore other retail options.

The high elasticity of m-commerce to the employment rate means that m-commerce, while increasing in popularity, has close substitutes. This is particularly so with the advent of immersive experiential marketing which aims to elevate shopping experience to new heights by focusing on both retail and entertainment ('retailtainment') and giving consumers a shopping experience beyond what they pay for. The employment rate also has a negative impact on other segments of B2C online sales (i.e., IRS_{it} , DOM_{it} , FOR_{it}) but with lower coefficients of elasticity (from -7.939% to -3.982%). Because products typically sold in B2C online commerce are nondurable goods (e.g., footwear, apparel, cosmetics, and food), these results are consistent with the earlier findings that nondurables spending is sensitive to changes in unemployment prospects (Côté and Johnson 1998).

Various model specifications present conflicting results on the direct impact of taxes tax_{it} on B2C online sales. Using different technology adoption measures and without controlling for time-invariant country characteristics, models on foreign internet retail sales FOR_{it} present empirical evidence on the negative impact of taxes (from -1.3777% to -0.989%). Meanwhile, employing fixed effects model controlled for credit card penetration and fixed telephone lines shows that taxes on FOR_{it} have positive and statistically significant impact (1.128% – 1.280%). This result is also evident in the impact of taxes on domestic retail sales, with coefficients ranging from 0.735% to 0.999% . The positive impact of taxes on B2C online commerce corroborates the findings of Baker, Johnson, and Kueng (2018) showing that shopping behavior of consumers in the United States is strongly responsive to changes in sales tax rates by spending more on online and cross-border shopping in both the short and long terms. The study finds that households shift spending to online merchants, which includes catalog and mail order sales, in the month following a sales tax increase, and this substitution persists in the long term.

The long-established negative impact of tariff on trade is also seen on B2C online sales, particularly internet retail sales IRS_{it} , m-commerce MOB_{it} , and domestic internet retail sales DOM_{it} with coefficients ranging from -0.171% to -0.119% . Although the B2C online sales are inelastic with respect to changes in tariffs, the negative relationship between the two implies that a lower tariff or openness to international trade leads B2C online sales to increase.

According to the estimation results, secondary education enrollment $educs_{it}$ confirms the findings of Burroughs and Sabherwal (2002) on the role that education level plays in internet retail sales IRS_{it} , with $educs_{it}$ generating positive and statistically significant coefficients. The high elasticity of these coefficients (3.833% – 6.629%) also suggests that internet retail sales IRS_{it} respond to changes in secondary education enrollment. The opposite results are observed on the impact of primary education enrollment $educp_{it}$ on B2C online sales. Various model specifications show that primary education enrollment has a negative and statistically significant impact on B2C online sales (from -7.903% to -2.105%). Overall, the results indicate that higher education facilitates B2C online commerce by increasing a population's ability to operate the electronic gadgets used in online shopping (personal computers, laptops, smartphones, tablets, and so on) and improving perceived ability to control uncertainty in adopting to technological innovations such as online shopping (Burroughs and Sabherwal 2002).

V. CONCLUSIONS

This paper reveals that strong and positive impact on B2C online commerce identified for both internet access and internet speed means that governments should widen focus on ICT policies supporting internet access for all to include ensuring its speed and stability. While several ICT-related policy actions by governments during the COVID-19 pandemic have focused on expanding access (WTO 2020), they should also pursue initiatives that will increase internet speed and ensure its stability and resilience amid shocks, such as the COVID-19 pandemic. School closures and stay-at-home policies have increased internet traffic from home. In effect, many users have experienced slower download speeds than before the pandemic-induced lockdown (Bergman and Iyengar 2020).

At a time the internet has become a lifeline, slow connections are not only an inconvenience and a source of frustration, they lead to productivity losses and missed opportunities. For businesses that shifted operations online during the COVID-19 pandemic, slow connections mean unstable video conferences and longer times to load e-mail and download files, undermining effective collaboration when working remotely. Poor internet performance also makes it difficult for businesses to explore the emerging market of applications and other opportunities in cloud computing.

Several news outlets have reported the rise in cybersecurity threats with unscrupulous marketers and criminals exploiting concerns about the COVID-19 pandemic as a bait for phishing attacks. This situation accentuates the implications this study finds about the importance of consumers' trust and secure internet servers in B2C online commerce. An SSL certificate protects the flow of information between the merchant's website to the customer's browser from eavesdropping. SSL also acts as a barrier against phishing by providing legitimate websites with a stamp of authority.

Another crucial implication is the urgency of financial inclusiveness. This study highlights the significance of access to the use of financial cards, particularly debit cards, in B2C online commerce. This implies that bank account and financial cards are among the key drivers of B2C online commerce. With the widespread closure of shops and banks at the height of the COVID-19 pandemic, online payments through bank accounts and financial cards facilitated B2C online transactions. Without access to these financial services, and with the physical transfer of cash discouraged to prevent the spread of the virus, the convenience and benefits of using B2C online commerce are beyond the reach of some people. And it is people who have no bank accounts or access to financial cards and other services who are likely to be the most vulnerable and hardest hit by the COVID-19 crisis. One measure to address this problem is for governments and financial regulators to alleviate barriers to access to credit services through, for instance, reducing intermediation costs and documentation requirements. Furthermore, governments and regulators can also set accounts with different limits and risks, and subsequently lower the costs and loosen the conditions for obtaining financial cards needed to buy online (Shirotori and Antunes 2020).

This study finds that internet access through fixed broadband internet subscription and mobile broadband subscription, online security, and financial inclusiveness are key factors behind the staggering growth of m-commerce in Asia and the Pacific in recent years. The pandemic has also led more consumers to turn to mobile shopping for groceries, daily necessities, and other products. The advent of wireless technologies such as mobile phones has led to an unprecedented rise in access to telecommunication services in Asia over the past 2 decades or so, even without adequate government investment on telecommunications infrastructure. The mobility, ease of use, and relatively low and declining costs of mobile phones have allowed vulnerable groups such as rural populations with low

incomes and literacy to experience the convenience and opportunities of telecommunication services. This highlights the crucial role of affordable wireless mobility devices and internet technology in allowing people with low incomes to gain the benefits of B2C online commerce.

The prevalence of B2C online commerce in every aspect of the economy and society is projected to continue as a long-term impact of the COVID-19 pandemic. B2C online commerce will need to continue to evolve to meet the challenges of the new normal. This study provides empirical evidence that technology adoption and financial inclusion issues do matter in facilitating B2C online commerce. Governments should then consider these important issues when planning strategies and policy frameworks that create an environment that helps B2C online commerce to adapt to the world after the COVID-19 crisis abates and ensure that it creates opportunities for all.

APPENDIX

Table A1.1: Data Description and Sources

Variable Name	Definition	Source
IRS_{it} : Internet retail sales	Sales of consumer goods (in \$) to the public through the internet including those from mobile phones and tablets.	Euromonitor International
MOB_{it} : Mobile internet retail sales	Sales of consumer goods (in \$) to the public through the internet using mobile devices such as smartphones and tablets.	Euromonitor International
DOM_{it} : Domestic internet retail sales	Sales of consumer goods (in \$) through the internet between domestic consumers and merchants.	Euromonitor International
FOR_{it} : Foreign internet retail sales (FOR_{it})	Sales of consumer goods (in \$) through the internet between domestic consumers and foreign merchants.	Euromonitor International
inf_{it} : Inflation	Annual percentage (%) change in price levels.	CEIC data, Haver Analytics, and national sources
tar_{it} : Simple mean applied tariff	This is the unweighted average of effectively applied rates for all products subject to tariffs (%) calculated for all traded goods.	World Bank, WDI
emp_{it} : Employment	ILO modeled estimates of employment to population ratio, 15+, total (%).	ILO database
tax_{it} : Tax	Taxes on goods and services (% value added of industry and services).	World Bank, WDI
server_{it} : Secure server	The number of distinct, publicly trusted TLS/SSL certificates found in the Netcraft Secure Server Survey.	World Bank, WDI
DC_{it} : Debit card penetration	The number of debit cards in circulation (excluding expired and withdrawn cards) of all financial institutions per 1,000 adults in the reporting jurisdiction.	IMF, Financial Access Survey
CC_{it} : Credit Card penetration	The number of credit cards in circulation (excluding expired and withdrawn cards) of all financial institutions per 1,000 adults in the reporting jurisdiction.	IMF, Financial Access Survey
educp_{it} : Net primary education enrollment rate	The ratio of children of official primary school age (as defined by the national education system) who are enrolled in primary school.	GCI
educs_{it} : Gross secondary education enrollment rate	The ratio of total secondary enrollment, regardless of age, to the population of the age group that officially corresponds to the secondary education level.	GCI
IUT_{it} : Internet Users	Percentage of individuals using the Internet.	ITU accessed from GCI
FBIS_{it} : Fixed-broadband internet subscription	Fixed broadband Internet subscriptions per 100 population. Fixed (wired) broadband subscriptions refers to the number of subscriptions for high-speed access to the public Internet (a TCP/IP connection).	ITU accessed from GCI
IIB_{it} : International internet bandwidth	International Internet bandwidth (kilobytes/second) per Internet user.	ITU accessed from GCI
MBS_{it} : Mobile broadband subscription	Active mobile broadband subscriptions per 100 population.	ITU accessed from GCI
MTS_{it} : Mobile telephone subscription	Number of mobile cellular telephone subscriptions per 100 population.	ITU accessed from GCI
FTL_{it} : Fixed telephone lines	Number of fixed telephone lines per 100 population.	ITU accessed from GCI

GCI = Global Competitiveness Index; ILO = International Labour Organization; IMF = International Monetary Fund; ITU = International Telecommunication Union; TLS/SSL = Transport Layer Security/Secure Socket Layers; WDI = World Development Indicators.

Source: Authors' compilation.

Table A1.2: Descriptive Analysis for All Variables

Variable	Number of Observations	Mean	Standard Deviation	Min	Max
<i>IRS_{it}</i> : Log(Internet retail sales)	57	13.87	2.69	7.90	19.69
<i>MOB_{it}</i> : Log(Mobile internet retail sales)	47	12.37	3.09	5.07	19.42
<i>DOM_{it}</i> : Log(Domestic internet retail sales)	48	13.91	2.76	6.92	19.61
<i>FOR_{it}</i> : Log(Foreign internet retail sales)	48	12.37	1.78	7.42	17.05
<i>inf_{it}</i> : Log(Inflation)	57	1.08	0.94	-1.20	2.69
<i>tar_{it}</i> : Log(Tariff)	57	6.18	3.03	0.17	12.03
<i>emp_{it}</i> : Log(Employment)	57	4.14	0.10	3.93	4.34
<i>tax_{it}</i> : Log(Tax)	57	1.63	0.37	1.04	2.74
<i>server_{it}</i> : Log(Secure server)	57	8.15	2.55	1.61	13.54
<i>DC_{it}</i> : Log(Debit card) (<i>DC_{it}</i>)	57	6.70	1.47	0.54	8.51
<i>CC_{it}</i> : Log(Credit Card) (<i>CC_{it}</i>)	49	5.02	2.35	-6.91	7.81
<i>educp_{it}</i> : Log(Primary enrollment)	57	4.54	0.05	4.44	4.61
<i>educs_{it}</i> : Log(Secondary enrollment)	57	4.42	0.21	3.92	4.72
<i>IUT_{it}</i> : Log(Internet Users)	57	3.50	0.99	0.07	4.52
<i>FBIS_{it}</i> : Log(Fixed-broadband internet subscription)	57	1.56	1.68	-4.50	3.45
<i>IIB_{it}</i> : Log(International internet bandwidth)	57	2.96	1.34	0.42	6.89
<i>MBS_{it}</i> : Log(Mobile broadband subscription)	55	2.96	1.87	-3.55	4.97
<i>MTS_{it}</i> : Log(Mobile telephone subscription)	53	4.62	0.55	2.41	5.23
<i>FTL_{it}</i> : Log(Fixed telephone lines)	53	2.47	1.14	-0.02	3.93

Source: Authors' estimation.

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The Role of Technology in Business-to-Consumer E-Commerce

Evidence from Asia

Using proprietary panel data, this paper investigates the possible drivers of business-to-consumer (B2C) online commerce growth. It provides empirical evidence that internet access and speed, online security, and financial inclusiveness facilitate internet retail sales. Governments can consider these findings as important issues in building an enabling environment for the development of B2C online commerce.

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