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# The impact of technology on access to credit: A review of loan approval and terms in rural Vietnam and Thailand



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### ABSTRACT

The acceleration of economic digitalisation has been immense in recent years, especially when coupled with the rapid development of technology-augmented finance. However, less understood is how such technology-augmented finance has impacted access to credit within rural contexts of developing economies. Using household-level survey data, our results provide novel evidence of a negative relationship, on average, between rural households' access to credit, as measured by loan approvals, and internet access. More specifically, use of internet in rural areas of the countries under analysis reduces the chance of accessing credit by up to 65%. Moreover, when we further investigate loan terms, our findings indicate that internet users get six-month shorter loan durations and have a lower interest cost of borrowing of up to 1.2%. The results for loan approval rates are persistent for formal loans and for nations at a lower stage of economic development, i. e., only within the less developed Vietnamese rural context. Our findings provide richer insights into the impact of information and telecommunication technologies (ITC) on access to finance in developing countries characterised by significant proportions of rural areas affected by severe information asymmetry-related issues that may be amplified or reduced by increased internet connectivity. Our results carry important policy implications. On the demand side, they highlight the need to ensure that government initiatives should aim to better educate rural borrowers in relation to financial literacy and credit choices. On the supply side, our findings urge the need to introduce policies for formal lenders targeted towards the reduction of the information asymmetries pervasive in rural areas.

# 1. Introduction

The acceleration of economic digitalisation has been immense over the past few years, leading to the rapid development of financial technologies (FinTech) across the entire spectrum of traditional financial services (Allen et al., 2021; Block et al., 2018). As a generative area of examination, these FinTech interventions have shown to reduce existing financial frictions such as information asymmetry, agency issues, and residual control rights furthering the development of our economic and welfare systems (Bollaert et al.,

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2021; Jakšič and Marinč, 2019; Sedunov, 2017). Many studies have explored how emergent financial technologies such as blockchain and digital credit have ameliorated access to finance (Bollaert et al., 2021; Farag and Johan, 2021). However, many of these studies are situated within a developed nation context where, it can be argued, the existing digital infrastructure has been able to, not only, keep pace but also support the adoption of these technologies thus accruing much of their benefit.

Less understood is how FinTech impacts access to finance in settings whereby the digital infrastructure is less developed and where measures of financial technology can be as simple as access to internet or a smartphone. This is where our study makes a novel contribution to the extant literature. Such settings are characterised with a low average per capita income, high dependence on agriculture, existence of climate-related risks, and poor infrastructure (Hardeweg et al., 2013). There is a growing body of development research that focuses on technology-augmented access to finance especially within rural settings in emerging markets (Abdulgadir and Asongu, 2022; Gimet and Lagoarde-Segot, 2012; N'dri and Kakinaka, 2020). Additionally, the current literature has rarely directly investigated the relationship between technology use as measured by internet connectivity and access to credit. We are aware of a stream of literature (Iver et al., 2015; Lin et al., 2012; Lin and Viswanathan, 2015; Rigbi, 2013; Wei and Lin, 2016; Xu et al., 2022; Zhang and Liu, 2012) that has explored the effects of the online loan market as a promising financing channel on people's economic behaviour but to the best of our knowledge, there is a scant literature directly investigating whether the use of the internet affects access to credit. Given this, our central hypothesis is a cross-country comparison of technology-augmented access to finance, where we concentrate our efforts on disentangling the relationship between internet access, as a proxy for financial technology, and rural households' credit access (Pham and Talavera, 2018). Our multi-country examination expands the scope to juxtapose two different sovereign situational contexts characterised by different degrees of economic development. We focus on Vietnam and Thailand as our backdrop for examination given their geographical proximity to each other and the similarities in terms of economic activity. Both nations are an appropriate field of study given their increasing levels of technological penetration and relative difficulties of individuals from rural settings in raising external finance, especially from formal sources. More so, given that, according to the World Bank, Thailand is classed a more economically developed that Vietnam – upper-middle and lower-middle income respectively – this provides for a natural control for economic development as a predictor of the effect of internet use on access to credit. We address our research question by exploiting households' survey data established by the longstanding Thailand Vietnam Socio Economic Panel over the period of 2016 - 2017. The dataset comprises over 4,400 rural households over 440 rural villages spread across six provinces in Vietnam and Thailand, collected using a three-stage procedure based upon the United Nations Department of Economic and Social Affairs guidelines (Arellano, Bond 1991; Basumatary et al. 2022; TVSEP 2024; World Bank Group 2016). We adopt a Lewbel (2012) methodology for our estimation and use the likelihood of loan approval as our dependent measure of rural access to credit. We further disentangle our analysis with additional examinations of credit terms, including interest cost of borrowing and loan maturity terms to provide a richer and deeper understanding of rural access to credit. Summarily, the Lewbel (2012) estimation methodology enables us to mitigate potential endogeneity concerns, and allows us to implement much of the endogeneity-robust controls of Arellano and Bond (1991) estimation methodologies such as two-stage least squares (2SLS) and generalised methods of moments (GMM) in the absence of adequate instrumentation. This is vital towards our study given the constraints of data within rural, emerging market settings.

We therefore contribute to the existing literature by investigating the relationship between internet connectivity and access to credit by households living in the rural settings of Vietnam and Thailand. To the best of our knowledge, no existing study has investigated such a nexus in rural settings, as much of the extant literature has focused either on developed countries or on the nonrural areas of developing economies. Specifically, by exploiting the exogeneous variation in local access to the internet that stems from the gradual geography-based roll-out of internet infrastructure across time and countries, we are able to convincingly estimate the causal impact of internet connectivity in the particular rural contexts of Vietnam and Thailand. Ceteris paribus, the spread of internet connectivity over less developed rural areas should indeed be associated with more pronounced economic effects for those rural regions that are further from their best practices, i.e., Vietnam. There is also a need to be mindful that there are observable differences between Vietnam and Thailand in terms of poverty levels and hence access to both technology and finance. Therefore, especially in Vietnam, internet access can be though not only as a rudimentary form of Fintech but also as a relatively more pronounced technological advancement with respect to wealthier developing countries that is likely to exert more significant effects on households' financing in the world (Chen et al., 2018).

Our results provide novel evidence of the negative relationship between rural households' access to credit and internet use. Such evidence holds only within a Vietnamese-context whilst our results indicate no links between internet access and credit access for Thailand. This runs contrary to conventional development literature on technology-augmented access to finance and we contend that there are potential issues of information asymmetry and overload in justifying this negative relationship (Bruhn and Love, 2014; Ortiz-Molina and Penas, 2008). Our key incremental contribution is rooted in the extension of the development literature and in the provision of a richer understanding of the relationship between technology and access to finance in rural settings within emerging markets (Mora-Rivera and García-Mora, 2021; N'dri and Kakinaka, 2020). Within such lower income settings, we contend that internet connectivity could present more substantial information technology and communication advancement that in wealthier environments. Our results are suggestive of this in indicating that there is no impact from internet on rural access to finance in nations with a higher economic level, i.e., Thailand. Moreover, we also contribute to the extant development literature by highlighting that technology negatively impacts rural loans that arise from formal sources. This is potentially indicative of changing demand-side preferences from rural borrowers coupled with increased information asymmetry borne from greater informational load from internet usage (Khuc et al., 2022). This has important policy implications, especially for government initiatives in promoting digital transformation and financial literacy, as well as strategies for financial intermediaries providing sources of formal finance. From a policy and strategy perspective, there is a need to ensure that centralised initiatives better educate rural borrowers in relation to financial literacy and credit choices. Whilst supply-side policies for formal lenders will have to be more targeted and focused to mitigate any potential

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# information asymmetry.

The remainder of our paper is organised as follows. Section two provides a review of the extant academic literature on internet access and access to finance setting the foundations of our hypothesis development. Section three details our methods of analysis and explains our adopted estimation methodology. Section four provides insight into our data and sample. We detail our empirical estimations in Section five and provide some narrative for the respective outputs, with our concluding remarks reported in Section six.

# 2. Literature review and hypothesis development

This paper contributes to the nascent yet growing remarkably rapidly empirical body of research that investigates the economic impact of modern infrastructure, such as internet and electricity, in developing and emerging economies (Hjort and Tian, 2021). Specifically, the scope of our study is to examine the economic consequences of households' adoption of internet connectivity by focusing on the rural settings of two developing countries, i.e., Vietnam and Thailand, characterised by very rudimentary forms of information and communication technologies (ICT). While for more developed countries internet use is common practice, for these developing countries, the advent of internet connectivity represents a milestone in ICT technological advancement, even more if considering their rural areas (Salemink et al., 2017). Indeed, nowadays not everyone can afford paying to connect to the Internet and those people who are left behind in the internet revolution are defined as being internet poor (World Bank Group, 2016). In developing countries, people who can afford internet connectivity are typically represented by highly educated business and professional people with high incomes. This issue is further exacerbated in less advanced rural settings characterized by a greater proportion of poor individuals.

# World Bank country classification by income level

GNI per capita in US\$ (Atlas methodology)





Fig. 1. World Bank country classification by income level. Source: World Bank database (2024).

The extant literature has provided evidence of a significant relationship between the spread of internet connectivity and countrylevel measures of economic progress. Indeed, the use of the internet has accounted for a great proportion of the economic progress of poor countries since the early 1980s (when the internet firstly appeared) and has rapidly grown afterwards with a concurrent acceleration of economic growth of the developing world in the 1980s and even more in the 1990s in tandem with the spread of internet connectivity. Nowadays, almost half the world has internet connectivity, of which 35% of Africans and 24% of South Asians, and internet access has accelerated especially in low-income countries with about 14 broadband subscriptions per 100 people (Hjort and Tian, 2021). Specifically, the introduction of technologies based on the internet (e.g., mobile payments, mobile loans, among others) has indeed led to crucial changes in the financial sector in the last decade, with significant effects on households' access to credit, boosting social welfare. In line with much of the extant development literature we delineate access to credit in relation to loan terms, more specifically loan amount, borrowing cost, and loan maturity, already used in rural settings (Giné, 2011; Khoi et al., 2013). The contention here is that technology-augmented access to finance is pro-growth and social welfare resulting in more competitive credit terms for borrowers (Beck et al., 2007). As argued by previous studies (Bruhn and Love, 2014; Honohan, 2004; Levine, 2005b) access to credit is important for economic growth with a significant positive relationship between credit access and poverty reduction at the country level. Specifically, Bruhn and Love (2014), focusing on Mexico, provide evidence that access to finance significantly affects labour market activity and income levels, especially in low-income individuals and among individuals living in areas characterised by smaller pre-existing bank penetration. Indeed credit facilitates access to liquidity and farm households to purchase productivity-enhancing inputs (such as improved seeds, fertilizers, and pesticides) (Kehinde and Ogundeji, 2022; Osabohien et al., 2020), invest in the farm and off-farm businesses (Ejemeyovwi et al., 2020), smooth household consumption throughout the business cycle (Kumar et al., 2020; Li et al., 2016), and cope with sickness prevention-related expenditures (Felkner et al., 2022) and children's education (Kandulu et al., 2019). There is also a large tranche of extant literature that highlights the impact of technology along demographical typologies such as gender and age. The assertion being that technology enables entities to acquire group-specific resources such as washers and sewing machines and other services necessary to keep enterprises (mainly micro-enterprises) as a going concern when other members of the household devote themselves to better or alternative salary opportunities (Basumatary et al., 2022; Datta and Sahu, 2020; Paudel et al., 2020).

The primary scope of this paper is, therefore, to contribute to this stream of literature by investigating the relationship between internet use and access to credit. This discussion leads us to develop the following first hypothesis being tested in this paper:

#### H1. Internet connectivity results in greater access to credit

Additionally, by drawing on the different World Bank classification of Thailand and Vietnam, we further exploit the heterogeneity of our cross-country dataset by separately testing whether there is a differential impact in the use of the internet on households' access to credit in Vietnam and Thailand, respectively. Indeed, according to the World Bank Vietnam is classified as a lower middle-income economy, whereas Thailand as an upper-middle income economy. The former economies are classified as those with a gross national income (GNI) per capita between \$1,036 and \$4,045, whereas upper middle-income economies are classified as those with a GNI per capita between \$4,046 and \$12,535 according to the World Bank classification, as shown in Fig. 1. The lower middle class is often made up of less educated people with lower incomes, such as managers, small business owners, teachers, and secretaries. The upper middle class is often made up of highly educated business and professional people with high incomes, such as doctors, lawyers, stockbrokers, and CEOs. A priori, based on previous studies, we would expect that ICT advances in the form of internet use might affect access to credit differently based on the country-specific development stage. In this respect, Fig. 2 shows the internet usage penetration in both Vietnam and Thailand and highlights the different stage of development with respect to the use of the internet for both countries, with Vietnam standing below Thailand in the time frame under analysis.

Within the rural contexts of Vietnam and Thailand, we focus on information frictions as one significant channel that can lead to either amplify or reduce the effects of internet connectivity on access to credit (Allen et al., 2021). Indeed, in the presence of severe



Fig. 2. Internet penetration rates (current and forecasts) for Vietnam and Thailand. Source: Statista (2024).

information asymmetries, decreasing in the degree of the country's development, and in the absence of trust and transparency, several transactions are not likely to be executed. This materializes even more in rural areas, such as our empirical setting, where a poor farmer experiences difficulties to access credit because the lender cannot evaluate their creditworthiness due to severe information asymmetries that make it difficult to accurately assess credit quality. In such a context, the internet reduces the costs of collecting, storing, processing, and exchanging information and makes a greater amount of information available transparently, thus should facilitate the occurrence of new transactions (Feyen et al., 2021; Goldfarb and Tucker, 2019). Mobile phone records, business-to business e-commerce, the sharing economy, online reputation mechanisms, and digital identification systems, made possible thanks to the advent of the internet, may help to mitigate information barriers between different parties. Moreover, existing evidence shows that, while these mechanisms render the market more efficient, the biggest benefit seems to be their market creation effects in terms of expanding trade, creating jobs, and increasing access to public services, thus promoting inclusion (World Bank Group, 2016). However, according to Graham and Foster (2016) the increased connectivity has had limited effect in reducing information inequality (e.g., contributions to Wikipedia mainly come from Hong Kong SAR and China, more than from all of Africa combined), despite the fact that Africa has 50 times more internet users. In fact, the information produced and consumed in the digital economy has little bearing on the number of users of digital technologies. Given that nearly one-fifth of the world's population is illiterate, the spread of digital technologies alone is unlikely to spell the end of the global knowledge divide (World Bank Group, 2016). This suggests that the benefits stemming from the use of the internet are not always grasped if the internet adoption is not accompanied by an appropriate degree of financial literacy of end-users. It follows that, for countries at lower stage of economic development, information asymmetries, could be exacerbated, rather than mitigated, by internet-related information overload and by a poor degree of financial and digital literacy of the population (Guo et al., 2024). This may lead to uninformed applications with unrealistic loan term demands and to a lack of trust of lending sources during the credit application process that, in turn, further widens the information asymmetry gap between lenders and borrowers thus resulting in lower loan approvals and poorer credit terms (Lin et al., 2012; Ortiz-Molina and Penas, 2008; Sharpe, 1990). This discussion leads us to the following second hypothesis being tested in this paper:

#### H2. There are country-level differences in the relationship between internet connectivity and access to credit.

Lastly, we further exploit the granularity of our data by distinguishing between access to formal and informal finance. Formal finance is financing capital that has been sourced from banks and other formal financial intermediaries, whereas informal finance is the capital which has been sourced from friends, family, relatives or private moneylenders (Elston et al., 2016). We therefore test for the effect of internet use on access to both formal and informal finance in both Vietnam and Thailand. This discussion leads us to the following third hypothesis being tested in this paper:

H3. Formal and informal access to credit is affected differently by internet connectivity.

#### 3. Data and sample

The source of the data utilized in this study is the "*Poverty dynamics and sustainable development: A long-term panel project in Thailand and Vietnam*," a long-term research project conducted in Thailand and Vietnam that aimed to establish a unique, multipurpose, and long-term socio-economic panel in two emerging economies.<sup>1</sup> The data utilised in this study is uniquely positioned to advance our understanding of issues pertinent to developing markets for various compelling reasons. Primarily, it comprises extensive household surveys executed longitudinally, enriching our socio-economic analysis with depth and temporal insights. Specifically, six provinces across Thailand and Vietnam—Buri Ram, Ubon Ratchathani, and Nakhon Phanom in Thailand, along with Ha Tinh, Thua Thien Hue, and Daklak in Vietnam—were meticulously chosen for their emblematic developing market features. These features include limited average per capita income, a heavy reliance on agriculture, vulnerability to climate risks, and underdeveloped infrastructure, as outlined by Hardeweg et al. (2013) and depicted in Fig. 3. Furthermore, the surveys' broad spectrum of variables, ranging from internet connectivity to financial access and conditions, furnish a comprehensive perspective on the socio-economic realities faced by rural populations.

Notably, the inclusion of data on internet usage is critical, as it allows for an in-depth exploration of how the digital divide influences financial inclusion within these rural locales. This examination is increasingly pertinent given the ongoing global shift towards digital economic frameworks. Additionally, the geographical focus on selected regions within Thailand and Vietnam amplifies the study's applicability to analogous settings in other developing countries. The strategic selection of these provinces, based on defined socio-economic parameters, ensures the data's encapsulation of the varied challenges and prospects prevalent in rural environments. Hence, this dataset not only facilitates an understanding of digital transformation's role in enhancing financial literacy and inclusion in developing nations but also underscores the potential effectiveness of policy interventions in these contexts. Through this lens, the study contributes significantly to the broader discourse on bridging economic disparities and fostering sustainable development within emerging economies.

The primary data collection utilised a three-stage procedure based on the United Nations Department of Economic and Social Affairs guidelines (United Nations, 2005). First, two districts were selected in each province. Second, two villages per district were chosen with probability proportional to the population size. Third, ten households per village were randomly selected from the list of all households in the sampled villages with equal probability. Prior to conducting the surveys, the interviewers underwent a rigorous selection process and received comprehensive training. The interviews were conducted at the respondents' residences and had an

<sup>&</sup>lt;sup>1</sup> This study relies on data from the long-term project No. 20220831434900116103, funded by the Deutsche Forschungsgemeinschaft (DFG). For more detailed information, see https://www.tvsep.de.



Fig. 3. Study sites in Thailand and Vietnam. Source: (Nguyen et al., 2020).

approximate duration of 2 hours. Following the interview, a separate interviewer and team leader reviewed each completed questionnaire for coherence and credibility. In cases where the collected data was inconsistent or conflicting, the responsible interviewer was required to re-collect the information either through telephone or by revisiting the households.

The research utilized a two-year panel dataset gathered in 2016 and 2017, which incorporated a dedicated section in the survey questionnaire asking households about their internet usage within the past 12 months. Specifically, the questionnaire enquired about the primary devices employed for Internet connectivity, as well as the main objectives for which the Internet was utilized. Another segment of the household questionnaire was devoted to probing saving and borrowing behaviours. With access to this comprehensive and informative survey data, the investigation aimed to scrutinize the effects of Internet utilization on financial access and conditions in the rural regions of Thailand and Vietnam.

Table 1 presents the descriptive statistics for the variables employed in this study. We use likelihood of rural household loan approval as our key dependent variable and further breakdown loan terms into the interest cost of borrowing and loan maturity. We also include the descriptive statistics for the loan amount, which we use as an alternative measure of rural access to credit as part of our robustness tests. Our sample data reveals that approximately 62–69% of households have been granted access to credit at least once during the survey period between Vietnam and Thailand respectively. Although borrowing rates in both countries are similar, borrowers in Thailand receive loan amounts that are three times higher than those in Vietnam. On average, a typical household in Thailand can obtain a loan of nearly 3.9 thousand PPP\$ 2005, while in Vietnam, the average loan amount is approximately 1.2 thousand PPP\$ 2005. This suggests that households in Thailand have access to more financial resources compared to their Vietnamese counterparts. Nonetheless, Vietnamese borrowers are subject to higher interest rates when borrowing for an average period of 15 months.

Regarding the use of the Internet, the study indicates that comparable percentages of households in both Thailand and Vietnam possess devices such as mobile phones, tablets, and computers to access the Internet. Our data sample demonstrates that 45 and 43 percent of households in Thailand and Vietnam, respectively, have the capability to access the Internet from home, with most of them using smartphones and computers. In terms of household head characteristics, the leaders of households in Thailand are comparatively older than those in Vietnam. Additionally, over 90 percent of household heads in both countries possess literacy skills, enabling them to acquire new knowledge and abilities from the Internet when it is accessible at home. Female household heads are not very prevalent in either country, with around 21 percent of household heads in Vietnam being female and 34 percent in Thailand.

In terms of household characteristics, a typical household in Thailand and Vietnam comprises of 5 members. However, households

# Table 1

Descriptive Statistics.

	Unit of measure	Whole sa	mple	Vietnam		Thailand	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Loan approval	dummy; 1 = Yes, 0 = No	0.658	0.474	0.626	0.484	0.69	0.462
Loan amount received	PPP\$ 2005	2616.20	7082.61	1273.81	2759.97	3935.57	9406.36
Interest rates	%	4.104	4.747	4.287	5.496	3.923	3.864
Loan maturity	months	14.809	13.838	15.402	15.466	14.226	11.999
Internet use	dummy; $1 = $ Yes, $0 = $ No	0.431	0.495	0.41	0.492	0.453	0.498
Age of household head	years	58.679	12.574	55.781	12.65	61.528	11.827
Household head can read or write	dummy; $1 = $ Yes, $0 = $ No	0.916	0.278	0.903	0.296	0.928	0.258
Household head is female	dummy; $1 = $ Yes, $0 = $ No	0.277	0.448	0.21	0.407	0.344	0.475
Size of household	no. of members	5.32	2.191	5.172	2.08	5.465	2.286
Dependency ratio	#	0.774	1.043	0.682	0.884	0.865	1.171
Member of socio-political organization	dummy; $1 = $ Yes, $0 = $ No	0.375	0.484	0.721	0.449	0.036	0.186
Total land of household	1000 m2	19.869	35.175	14.252	39.736	25.389	28.989
Average years of schooling	years	7.727	2.781	8.151	2.99	7.311	2.49
Suffer from an unexpected shock	dummy; $1 = $ Yes, $0 = $ No	0.704	0.456	0.743	0.437	0.666	0.472
Number of businesses	#	0.369	0.659	0.386	0.667	0.351	0.652
Monthly wages	PPP\$ 2005	455.177	592.807	240.036	283.724	666.628	726.331
Total asset values	PPP\$ 2005	4618.75	9625.85	1864.82	3205.97	7325.44	12,604.07
Distance to VBARD / BAAC travel	km	9.406	8.638	7.308	8.762	11.467	7.997
Distance to VBSP / Agric Coop. travel	km	10.349	9.107	7.617	8.795	13.034	8.597
Distance to Credit organization/GCB travel	km	9.413	10.775	3.853	8.846	14.877	9.649
Distance to other commercial banks No. of observations	km	12.897 7630	12.379	10.704 3782	14.057	15.053 3848	10.016

in Vietnam have a lower proportion of children and elderly people compared to households in Thailand. Moreover, a large proportion of households in Vietnam (about 72%) have reported having at least one member in a social-political organization, which is significantly higher than the corresponding figure for Thailand at 4%. This is attributed to the Vietnamese population's active participation in social and political groups to expand their social networks, as per Chung et al. (2020). Additionally, households in Thailand seem to have more land resources, with an average of 2.5 ha compared to 1.4 ha in Vietnam. With respect to shocks, Vietnamese households are more likely to be exposed to negative shocks than their Thai counterparts, with 74% of households in Vietnam experiencing at least one negative event as compared to 67% in Thailand. Furthermore, Vietnamese households have higher average years of schooling (around 8 years) than households in Thailand (around 7 years). However, in terms of total asset values and monthly wages, households in Thailand is over 7.3 thousand \$PPP 2005, which is four times higher than that of a Vietnamese household. Lastly, the average distance from a household to the nearest credit institution is approximately 10 kilometres for both Thailand and Vietnam.

Table 2 provides additional information concerning the means by which the rural populace in Thailand and Vietnam gain entry to the internet. Smartphones and computers are identified as the primary devices utilized by rural households for this purpose. These technologically advanced devices afford approximately 41 percent of the sampled households the opportunity to connect to the worldwide web. The usage of tablets or internet cafes to access the internet is relatively low, with approximately 2 percent of households relying on these methods. Our collected sample data indicates that nearly 57 percent of households are without access to the internet.

Table 3 presents a comparison of household characteristics between two distinct population groups: those who use the internet and those who do not. The typical age of household heads in the group of internet users is approximately 56 years, while the mean age in

## Table 2

Key devices for household internet usage.					
Main device for connecting to internet	No. of households with this device	Percent			
Smartphone	2771	36.32			
Computer (PC and/or laptop)	400	5.24			
Tablet	52	0.68			
Others (from internet cafes)	68	0.89			
No access	4339	56.86			
Total	7630	100			

the group of non-users is four years higher. This difference can be explained by the fact that older individuals are less likely to use the internet to obtain information and prefer to rely on relatives or traditional printed media.

Households with internet access generally have larger sizes and a smaller proportion of children and elderly individuals. This association can be linked to the fact that the working-age population is more inclined to use the internet for purposes such as job searches, education, and social networking. Additionally, internet users are likely to have more land, assets, and income from wages than non-users, suggesting that households with greater wealth are more likely to have internet access due to their ability to afford the cost of devices such as computers or smartphones and subscription fees for internet connectivity. Moreover, households with internet access are less vulnerable to unexpected events or disturbances.

# 4. Methodology

To commence our empirical examination, we initiated the estimation of the influence of internet usage on rural access to finance. We utilise likelihood of loan approvals as our core dependent variable. Loan approval is a key indicator of financial access, as it represents the ability of individuals to obtain credit from financial institutions and is utilised in much of the development literature when examining credit access (Behr and Sonnekalb, 2012; Popov and Udell, 2012). Internet use may have a positive impact on loan approval rates by providing borrowers with greater access to information and resources needed to successfully apply for loans. Given the nature of the casual relationships, the effects of internet use on financial access and terms are estimated by following model:

$$F_{it} = \lambda + \theta I_{it} + \beta H_{it} + \epsilon_{it},\tag{1}$$

where *F* stands for rural access to finance. *I* represents the indicator of whether the household is an internet user or not. *H* is the vector of control variables, including household characteristics, and *e* represents the error term. Following the literature (Asiedu et al., 2012; Behr et al., 2011; Behr and Sonnekalb, 2012), we further enrich our examination with a consideration for the loan terms of those who have received access to credit and include both the interest cost of borrowing and the loan maturity as separate measures of credit terms. Interest rates are a crucial determinant of the cost of credit and can significantly affect borrowers' ability to repay loans. Internet use may allow borrowers to compare interest rates across different lenders and loan products and make more informed borrowing decisions that lead to lower interest rates. Furthermore, loan maturity refers to the length of time borrowers have to repay their loans and can impact their ability to manage their debt and meet their financial obligations. Internet use may enable borrowers to access loan products with more flexible repayment terms, which could improve their ability to manage their debt and meet their financial colligations.

Eq. (1) incorporates the independent variable, internet use (*I*), which is likely to be endogenous due to various reasons. One of these reasons is reverse causality, which arises when a change in internet use is caused by accessing finance, rather than the other way around. For instance, individuals who borrow money may tend to use the internet more to conduct their businesses. In addition, the presence of other variables that affect both internet use and the outcome variable, but are not accounted for in the model, may also render internet use an endogenous variable. This could be the case if households with more free time tend to use the internet more, and if free time also affects the outcome variable. Measurement error is another factor that could contribute to endogeneity. If individuals who are more motivated to achieve tend to overestimate their internet use, and motivation also influences the outcome variable, then internet use may be endogenous. Simultaneity is also a factor contribute to the issue. variables like literacy and schooling could simultaneously influence a household's decision or ability to use the internet use may also be endogenous. For instance, if individuals who are more extroverted tend to use the internet more, and extroversion also impacts the outcome variable, then internet use would be an endogenous variable.

Previous research has demonstrated that household characteristics have a significant impact on internet usage (Briggeman and

# Table 3

Household characteristics by internet use.

	Unit of measure	Internet non- users	Internet users	Coefficients	p-values
Age of household head (years)	years	60.345	56.483	3.862	0.000***
Household head can read or write (1 for yes, 0 otherwise)	dummy; $1 = $ Yes, $0 = $ No	0.892	0.948	-0.056	0.000***
Household head is female (1 for female, 0 otherwise)	dummy; 1 = female, 0 =	0.296	0.252	0.044	0.000***
	male				
Size of household (number of members)	no. of members	5.076	5.641	-0.566	0.000***
Dependency ratio (#)	#	0.863	0.657	0.205	0.000***
Member of socio-political organization (1 for yes, 0 otherwise)	dummy; $1 = $ Yes, $0 = $ No	0.385	0.363	0.023	0.041**
Total land of household (1000 m2)	1000 m <sup>2</sup>	18.029	22.295	-4.266	0.000***
Average years of schooling (years)	years	6.958	8.742	-1.784	0.000***
Suffer from an unexpected shock (1 for yes, 0 otherwise)	dummy; $1 = $ Yes, $0 = $ No	0.717	0.688	0.029	0.006***
Number of businesses (#)	#	0.261	0.51	-0.249	0.000***
Monthly wages (PPP\$ 2005)	PPP\$ 2005	373.615	562.711	-189.097	0.000***
Total asset values (PPP\$ 2005)	PPP\$ 2005	2736.90	7099.86	-4362.96	0.000***
No. of observations		4339	3291		

Notes: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Household characteristics are in at means. T test is conducted for the differences in means.

## Table 4

Assumption tests for heteroskedasticity-based instrument models.

	Breusch-Pagan test	Pagan and Hall test
Loan approval	0.000	0.000
Loan amount received	0.029	0.000
Interest rates	0.000	0.000
Loan maturity	0.000	0.000

*Notes*: Household characteristics are in at means. Breusch–Pagan test, the null hypothesis (H0): Constant variance. Pagan and Hall test, the null hypothesis (H0): Disturbance is homoscedastic. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Whitacre, 2010; Mesch and Talmud, 2011; Nguyen et al., 2023; Yang et al., 2021). In order to tackle these concerns, we employ the heteroscedasticity-based instrumental variable (IV) method developed by Authur Lewbel (2012). This involves modelling the household's decision to utilize the internet under the assumption that:

$$I_{it}=\gamma+\delta Z_{it}+\xi_{it},$$

(2)

where  $\xi$  stands for the residuals and Z are exogenous household characteristics (age, gender of household head, literacy of household head, household size, and average schooling years). With suggestion from Lewbel (2012), we can use  $[Z'_{it} - E(Z'_{it})]\widehat{\xi_{it}}$  as instruments (IVs). These instruments are derived from the discrepancies observed in the initial regression stage, specifically if they exhibit heteroskedasticity. They are formulated by taking the squared residuals from the equations after regression and then multiplying them with every exogenous variable present in the regression. The stronger the correlation between these instruments and the endogenous variables they are paired with (indicating a more effective instrument), the greater the extent of heteroskedasticity in the error process. Instruments are newly created using all the exogenous regressors, fashioned through regressors that do not correlate with the heteroskedastic error products.

These generated instruments are valid as soon as two assumptions are satisfied: (1)  $Cov(Z_{it}, \epsilon_{it} = 0 \text{ and } (2) Cov(Z_{it}, \xi_{it}^2) \neq 0$ . The first assumption is to ensure the IVs are uncorrelated with the error term in Eq. (1). The later assumption is to guarantee that IVs are correlated with  $I_{it}$  through  $\xi_{it}$ . The Pagan and Hall test as well as the Breusch-Pagan test were employed to examine the aforementioned assumptions, in line with the methodology of Baum and Lewbel (2019) study. Table 4 reports these tests on the two assumptions. The results indicate that both assumptions were met.

To further validate our models, various post-estimation tests were conducted to assess under identification, over identification, and weak identification, as per the approach of Staiger and Stock (1997). The outcomes of these tests, as presented in Table 1, serve to affirm the soundness of our models. Moreover, as a means of ensuring the reliability and validity of our findings, this study employs an alternative measure of the key dependent variable as a test of sensitivity of our estimation outputs, loan amount. In terms of estimation method, we employ Propensity Score Matching in combining with Difference in Difference to investigate the influence of internet use on financial access and terms as our robustness check.

# 5. Results

# 5.1. Baseline results

Table 5 reports the baseline estimations for the impacts of internet use on financial access and terms. Panel (a) in Table 5 presents our estimation outputs for our core dependent measure of rural access to finance – likelihood of loan approval – whilst panels (b) and (c) are our additional examinations of loan terms as measured by the interest cost of borrowing and loan maturity respectively. All models are run with heteroskedastic robust standard errors and two-way fixed effects controlling for both year and country dynamics to mitigate the issue of unobserved heterogeneity. Additionally, diagnostics for standard IV-based regressions have also been undertaken, including the use of Kleibergen-Paap LM test for under-identification, the Hansen J test for over-identification, and the Cragg-Donald Wald F statistics to measure weak identification. The test statistics presented in Table 5 are supportive of the use of our heteroskedasticity-based instruments.

From Table 5, panel (a), our baseline estimations are indicative of a significant, negative relationship between internet use and our three measures of interest within our study. This suggests that internet usage is a negative predictor of likelihood of loan approvals, whilst at the same time diminishing the loan terms for borrowers as measured by cost of borrowing and term of borrowing. More specifically, using internet in rural areas of the countries in ASEAN reduces the chance of accessing credit up to 65 percent. Panels (b) and (c) highlight the results of our further delineation of technology and rural access to credit with a deeper examination of the terms of approved household loans. Our estimation outputs indicate that internet users get six month shorter loan durations. Additionally, it is worthy to note that households with access to internet have a lower interest cost of borrowing of up to 1.2 per cent.

Our findings are intriguing as they run contrary the a priori hypothecation established from the extant academic literature. We offer an explanation along the following lines. Firstly, drawing on the credit demand and information asymmetry literature (Bruhn and Love, 2014; Honohan, 2004; Levine, 2005a). It is possible that individuals who have greater access to the internet may encounter information overload thus making uninformed applications with unrealistic loan term demands. Secondly, along similar lines, the informational overload could also lead to a lack of trust of lending sources during the credit application process. This lack of trust

#### Table 5

Impact of internet use on credit access and terms.

$ \begin{array}{ c c c c c c } \hline (a) & (b) & (c) \\ \hline Loan Approval & Interest rates & Loan Maturity \\ \hline Internet use & -0.6547^{***} & -1.2584^* & -6.1411^{***} \\ (0.2095) & (0.6886) & (2.1500) \\ \hline Age of household head & -0.0201^{***} & -0.0600^{***} & -0.1849^{***} \\ (0.0013) & (0.0049) & (0.0142) \\ \hline Household head can read or write & -0.0082 & 0.066 & -0.5228 \\ (0.0566) & (0.2039) & (0.5821) \\ \hline Household head is female & -0.0303 & -0.2455^{**} & 0.0876 \\ (0.0364) & (0.1232) & (0.3708) \\ \hline Size of household & 0.0766^{***} & 0.2149^{***} & 0.7554^{***} \\ (0.0089) & (0.0308) & (0.0920) \\ \hline Dependency ratio & -0.0449^{***} & -0.1788^{***} & -0.4383^{***} \\ \hline Member of socio-political organization & -0.0858^{**} & -0.0713 & 0.9975^{***} \\ \hline \end{array}$		Heteroscedasticity-based instruments			
Internet use $-0.6547^{***}$ $-1.2584^{*}$ $-6.1411^{***}$ (0.2095)(0.6886)(2.1500)Age of household head $-0.0201^{***}$ $-0.0600^{***}$ $-0.1849^{***}$ (0.0013)(0.0049)(0.0142)Household head can read or write $-0.0082$ $0.066$ $-0.5228$ (0.0566)(0.2039)(0.5821)Household head is female $-0.0303$ $-0.2455^{**}$ $0.0876$ (0.0364)(0.1232)(0.3708)Size of household $0.0766^{***}$ $0.2149^{***}$ $0.7554^{***}$ (0.0089)(0.0308)(0.0920)Dependency ratio $-0.0449^{***}$ $-0.1788^{***}$ $-0.4383^{***}$ (Member of socio-political organization $-0.0858^{**}$ $-0.0713$ $0.9975^{***}$		(a) Loan Approval	(b) Interest rates	(c) Loan Maturity	
(0.2095)         (0.6886)         (2.150)           Age of household head         -0.0201**         -0.0600**         -0.1849**           (0.0013)         (0.0049)         (0.0142)           Household head can read or write         -0.0082         0.066         -0.5228           (0.0566)         (0.2039)         (0.5821)           Household head is female         -0.0303         -0.2455*         0.0876           (0.0364)         (0.1322)         (0.3708)           Size of household         0.0766***         0.2149***         0.7554***           Opendency ratio         -0.0449***         -0.1788***         -0.4383***           Member of socio-political organization         -0.0858**         -0.0713         0.9975**	Internet use	-0.6547***	-1.2584*	-6.1411***	
Age of household head         -0.0201***         -0.0600***         -0.1849***           Index (0.0013)         (0.0049)         (0.0142)           Household head can read or write         -0.0082         0.066         -0.5228           Index (0.0566)         (0.2039)         (0.5821)           Household head is female         -0.0303         -0.2455**         0.0876           Index (0.0566)         (0.1232)         (0.3708)           Size of household         0.0766***         0.2149***         0.7554***           Index (0.0689)         (0.0308)         (0.0920)           Dependency ratio         -0.0449***         -0.1788***         -0.4383***           Index (0.0166)         (0.0562)         (0.1632)           Member of socio-political organization         -0.0858**         -0.0713         0.9975**		(0.2095)	(0.6886)	(2.1500)	
(0.0013)         (0.0049)         (0.0142)           Household head can read or write         -0.0082         0.066         -0.5228           (0.0566)         (0.2039)         (0.5821)           Household head is female         -0.0303         -0.2455**         0.0876           (0.0364)         (0.1232)         (0.3708)           Size of household         0.0766***         0.2149***         0.7554***           0.0089)         (0.0308)         (0.0920)           Dependency ratio         -0.0449***         -0.1788***         -0.4383***           Member of socio-political organization         -0.0858**         -0.0713         0.9975***	Age of household head	-0.0201***	-0.0600***	-0.1849***	
Household head can read or write       -0.0082       0.066       -0.5228         (0.0566)       (0.2039)       (0.5821)         Household head is female       -0.0303       -0.2455**       0.0876         Size of household       (0.0364)       (0.1232)       (0.3708)         Dependency ratio       0.0089)       (0.0308)       (0.0920)         Dependency ratio       -0.0449***       -0.1788***       -0.4383***         Member of socio-political organization       -0.0858**       -0.0713       0.9975**		(0.0013)	(0.0049)	(0.0142)	
(0.0566)         (0.2039)         (0.5821)           Household head is female         -0.0303         -0.2455**         0.0876           (0.0364)         (0.1232)         (0.3708)           Size of household         0.0766***         0.2149***         0.7554***           (0.0089)         (0.0308)         (0.0920)           Dependency ratio         -0.0449***         -0.1788***         -0.4383***           Member of socio-political organization         (0.0858**         -0.0713         0.9975***	Household head can read or write	-0.0082	0.066	-0.5228	
Household head is female         -0.0303         -0.2455**         0.0876           (0.0364)         (0.1232)         (0.3708)           Size of household         0.0766***         0.2149***         0.7554***           (0.0089)         (0.0308)         (0.0920)           Dependency ratio         -0.0449***         -0.1788***         -0.4383***           (0.0166)         (0.0562)         (0.1632)           Member of socio-political organization         -0.0858**         -0.0713         0.9975**		(0.0566)	(0.2039)	(0.5821)	
(0.0364)         (0.1232)         (0.3708)           Size of household         0.0766***         0.2149***         0.7554***           (0.0089)         (0.0308)         (0.0920)           Dependency ratio         -0.0449***         -0.1788***         -0.4383***           (0.0166)         (0.0562)         (0.1632)           Member of socio-political organization         -0.0858**         -0.0713         0.9975**	Household head is female	-0.0303	-0.2455**	0.0876	
Size of household         0.0766***         0.2149***         0.7554***           (0.0089)         (0.0308)         (0.0920)           Dependency ratio         -0.0449***         -0.1788***         -0.4383***           (0.0166)         (0.0562)         (0.1632)           Member of socio-political organization         -0.0858**         -0.0713         0.9975**		(0.0364)	(0.1232)	(0.3708)	
(0.0089)         (0.0308)         (0.0920)           Dependency ratio         -0.0449***         -0.1788***         -0.4383***           (0.0166)         (0.0562)         (0.1632)           Member of socio-political organization         -0.0858**         -0.0713         0.9975***           (0.020)         (0.2700)         (0.2700)         (0.2700)	Size of household	0.0766***	0.2149***	0.7554***	
Dependency ratio         -0.0449***         -0.1788***         -0.4383***           (0.0166)         (0.0562)         (0.1632)           Member of socio-political organization         -0.0858**         -0.0713         0.9975***           (0.0201)         (0.1210)         (0.2700)         (0.2700)		(0.0089)	(0.0308)	(0.0920)	
(0.0166)         (0.0562)         (0.1632)           Member of socio-political organization         -0.0858**         -0.0713         0.9975***           (0.0261)         (0.1210)         (0.2700)	Dependency ratio	-0.0449***	-0.1788***	-0.4383***	
Member of socio-political organization $-0.0858^{**}$ $-0.0713$ $0.9975^{***}$ (0.0241)         (0.1210)         (0.2700)		(0.0166)	(0.0562)	(0.1632)	
(0.0261) (0.1210) (0.2790)	Member of socio-political organization	-0.0858**	-0.0713	0.9975***	
(0.0301) $(0.1310)$ $(0.3789)$		(0.0361)	(0.1310)	(0.3789)	
Total land of household         0.0005         0.0022         0.0065	Total land of household	0.0005	0.0022	0.0065	
(0.0007) (0.0021) (0.0064)		(0.0007)	(0.0021)	(0.0064)	
Average years of schooling 0.0195** 0.0586* 0.3787***	Average years of schooling	0.0195**	0.0586*	0.3787***	
(0.0089) (0.0305) (0.0921)		(0.0089)	(0.0305)	(0.0921)	
Suffer from an unexpected loss 0.3240*** 0.7681*** 2.6649***	Suffer from an unexpected loss	0.3240***	0.7681***	2.6649***	
(0.0378) (0.1178) (0.3639)	1	(0.0378)	(0.1178)	(0.3639)	
Number of businesses -0.0011 -0.033 0.2892	Number of businesses	-0.0011	-0.033	0.2892	
(0.0268) (0.0923) (0.2747)		(0.0268)	(0.0923)	(0.2747)	
Log of monthly wages 0.0342*** 0.0463** 0.3303***	Log of monthly wages	0.0342***	0.0463**	0.3303***	
(0.0059) (0.0209) (0.0611)	0 , 0	(0.0059)	(0.0209)	(0.0611)	
Log of total asset values 0.1178*** 0.2413*** 0.8812***	Log of total asset values	0.1178***	0.2413***	0.8812***	
(0.0219) (0.0758) (0.2405)	0	(0.0219)	(0.0758)	(0.2405)	
Distance to VBARD / BAAC travel time 0.0047 0.0162** 0.0344	Distance to VBARD / BAAC travel time	0.0047	0.0162**	0.0344	
(0.0032) (0.0082) (0.0261)		(0.0032)	(0.0082)	(0.0261)	
Distance to VBSP / Agric Coop. travel time 0.0031 0.0075 0.0417	Distance to VBSP / Agric Coop. travel time	0.0031	0.0075	0.0417	
(0.0029) (0.0082) (0.0257)		(0.0029)	(0.0082)	(0.0257)	
Distance to Credit organization/GCB travel time $-0.0014$ $-0.0287^{***}$ $-0.0796^{***}$	Distance to Credit organization/GCB travel time	-0.0014	-0.0287***	-0.0796***	
(0.0022) (0.0066) (0.0195)		(0.0022)	(0.0066)	(0.0195)	
Distance to other commercial banks 0.0027* 0.0227*** 0.0458***	Distance to other commercial banks	0.0027*	0.0227***	0.0458***	
(0.0016) (0.0059) (0.0166)		(0.0016)	(0.0059)	(0.0166)	
No. of observations 7630 7630 7630	No. of observations	7630	7630	7630	
Under identification test 0 0 0 0	Under identification test	0	0	0	
<b>Over identification test</b> 0.1121 0.1301 0.015	Over identification test	0.1121	0.1301	0.015	
Weak identification test         46.809         26.765         26.765	Weak identification test	46.809	26.765	26.765	

*Notes*: Robust standard errors in parentheses. The under-identification test is an LM test based on Kleibergen and Paap (2006) rk LM statistics with the null hypothesis that the model is under identified. The over identification test is based on the Hansen J test with the null hypothesis that all instruments are valid. For weak identification, Cragg–Donald Wald F statistics are reported. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

widens the information asymmetry gap between lenders and borrowers thus resulting in lower loan approvals (Lin et al., 2012; Ortiz-Molina and Penas, 2008; Sharpe, 1990). This widening of the information asymmetry gap via a lack of trust can also be exacerbated by the degree of financial and digital literacy within such rural settings within emerging markets. This could lead to lower financial access and less favourable loan terms, as these borrowers may not be aware of all the options available to them and proliferate decisions-based upon a narrow knowledgebase.

Regarding the control variables, our findings indicate that the age of household heads, dependent ratio, and membership in socialpolitical organizations are associated with adverse impacts on access to financial services. Older household heads may have lower incentives for business activities and borrowing credit, which can be exacerbated as they approach retirement age, leading financial institutions to perceive them as higher risk borrowers. Furthermore, limited earning potential and fixed income may hinder their ability to access financial services or qualify for loans, and a lack of recent credit activity or history of missed payments may also lower their credit score. The dependent ratio, reflecting the ratio of dependents to working-age individuals, may also impact access to financial services as households with a higher ratio may have less disposable income to allocate toward loan repayments, which could increase their perceived risk and lead to lower loan amounts. Additionally, membership in social-political organizations may be perceived as a higher risk of default by lenders, resulting in lower loan amounts and shorter loan durations being offered to these individuals (Li et al., 2023; Shi and Du, 2024). Given the rural settings, we also control for geo-spatial effects of key formal lending institutions as represented by distance to development banks (VBARD/BAAC), agricultural cooperatives, credit organisations, and commercial banks. We observe some positive effects for commercial banks, and we explore this further in the following sections as we are aware of both further country differences, and formal and information sources of credit for rural access to finance.

## 5.2. Country-level breakdown of types of borrowing

We disentangle our baseline regressions further at a country-level stratification and then also at a type of borrowing level and present the results in Table 6. Do note that all models are run as heteroskedastic-based instrumental estimations, with robust standard errors and two-way fixed effects at both period and country-level. All models in the Table 6 are run with full specifications of control variables indicated in Eq. (1), however for brevity and tractability we have chosen to not report this.

Panels (a) - (c) and (d) - (f) are the estimation outputs for Thailand and Vietnam respectively. From panels (a) and (d) we observe that the negative effects of internet use on loan approval and loan terms are concentrated solely within a Vietnamese context. As indicated within our literature review, a possible explanation for this could be borne from the additional information asymmetry borne from a lower level of economic development for Vietnam than Thailand - lower-middle compared to upper-middle income nation. Additionally, the lack of a relationship between internet usage and access to credit for Thailand is also interesting in that we cannot conclusively say that greater access to internet as a measure of technology has any impact on both access to credit and credit terms for the borrower.

In Vietnam, the phenomenon of information asymmetry, especially concerning internet use and financial access, is significantly contributes to the adverse outcomes observed in our research. First, despite Vietnam's rapid internet growth, a digital divide persists, with rural areas having limited access compared to urban centres. This divide is not merely about connectivity but also pertains to the quality and utility of internet use. Rural populations, therefore, might not benefit fully from the internet's potential to enhance financial literacy and access due to this divide (Pearce, 2020). Second, financial literacy in Vietnam shows considerable variation across different demographics, with significant gaps noted between urban and rural populations. A survey by the Vietnam Central Bank in 2019 highlighted that only a fraction of the rural population has basic financial knowledge compared to their urban counterparts. This disparity in financial literacy exacerbates information asymmetry as individuals in rural areas are less informed about financial products and services, impacting their interactions with the formal financial sector (Khuc et al., 2022; Quang and Anh, 2019). Moreover, the reliance on informal financial networks in rural Vietnam further complicates this landscape. While these networks are critical for financial access in areas poorly served by formal institutions, they operate based on personal trust and do not necessarily provide the same level of transparency and consumer protection as formal financial services. This reliance can perpetuate information asymmetry, as individuals may lack awareness or be wary of formal financial options (Dufhues, 2007; Khoi et al., 2013). These factors collectively contribute to a scenario where the potential benefits of internet use in bridging information gaps and enhancing financial access are undermined by the existing digital and financial literacy divide, alongside a deeply entrenched informal financial system. Such a context provides a fertile ground for information asymmetry to thrive, which could explain the negative effects of internet use on financial access observed in our analysis. Addressing these underlying issues is crucial for leveraging the internet as a tool for financial inclusion in Vietnam.

We breakdown types of loans into formal and informal borrowing (Giné, 2011; Khoi et al., 2013) for both Thailand and Vietnam in panels (b) - (c) and (e) - (f) respectively. Once again, we observe that the significant effects of internet use and our measures of access to credit and credit terms are only persistent within the Vietnamese context. Importantly, our results indicate that internet usage has a

# Table 6

Additional estimation stratified at country-level and types of loans.

	Heteroscedasticity-based instruments			Heteroscedasticity-based instruments			
	Loan Approve Panel (a): Full samp	Interest rates ple of Thailand	Loan Maturity	Loan Approve Panel (d): Full samp	Interest rates le of Vietnam	Loan Maturity	
Internet use	-0.1173	0.5375	-0.5895	-0.5635**	-1.0662	-5.3000**	
	(0.4539)	(0.9282)	(3.0254)	(0.2588)	(0.8600)	(2.5459)	
No. of observations	3848	3848	3848	3782	3782	3782	
Under identification test	0	0	0	0	0	0	
Over identification test	0.024	0.039	0.429	0.115	0.038	0.306	
Weak identification test	10.613	10.613	10.6123	17.157	17.157	17.157	
	Panel (b): Sample of formal credit in Thailand			Panel (e): Sample of formal credit in Vietnam			
Internet use	-0.0413	0.6037	1.3266	-0.6523**	-0.8238	-6.6900**	
	(0.4317)	(0.8291)	(2.7743)	(0.2844)	(0.9011)	(2.8108)	
No. of observations	3571	3571	3571	3357	3357	3357	
Under identification test	0	0	0	0	0	0	
Over identification test	0.029	0.178	0.578	0.107	0.0481	0.1221	
Weak identification test	11.002	11.002	11.002	15.098	15.098	15.098	
	Panel (c): Sample o	f informal credit in T	hailand	Panel (f): Sample of informal credit in Vietnam			
Internet use	-0.2744	-0.3347	-2.6781	-0.3216	-1.1997**	-2.8824*	
	(0.3627)	(0.8219)	(3.4790)	(0.2455)	(0.5680)	(1.6642)	
No. of observations	1469	1469	1469	1839	1839	1839	
Under identification test	0	0	0	0	0	0	
Over identification test	0.946	0.559	0.862	0.288	0.478	0.805	
Weak identification test	10.749	10.749	10.749	22.122	22.122	22.122	

*Notes*: Robust standard errors in parentheses. The under-identification test is an LM test based on Kleibergen and Paap (2006) rk LM statistics with the null hypothesis that the model is under identified. The over identification test is based on the Hansen J test with the null hypothesis that all instruments are valid. For weak identification, Cragg–Donald Wald F statistics are reported. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

negative effect on formal loan approval rates with a 65% drop in the likelihood of receiving formal credit. We observe no effect on the approval rates of informal loans. Examining loan terms, our results indicate reduced loan maturities for both formal and informal loans -6.7 months and 2.9 months respectively – whilst internet access has a positive effect on the informal cost of borrowing potentially suggestive of either improved demand-side bargaining power or greater understanding of supply-side market forces and competition with formal loans. This provides a richer insight into the impact of technology on access to finance in rural settings in that increased internet usage is seen to be inconsequential for informal borrowing. That technology has an impact on access to formal finance in rural settings once again extends our a priori understanding within the development literature and could be suggestive that the formal lending infrastructure and governmental policies for increased access to finance from formal sources have had some impact on rural borrowing (Chichaibelu and Waibel, 2017). We can extend this line of contention when examining the Vietnamese results - panel (f) for informal loan sources where increased internet use impacts the informal loan terms - reducing the informal cost of borrowing and the term of the informal loan. This could be indicative of changing demand- and supply-side dynamics with greater internet usage augmenting rural borrowers' perceptions of the options available to them from formal credit that cannot be met from informal lending sources thus resulting in lower informal cost of borrowing and reduced informal loan terms (Mora-Rivera and García-Mora, 2021). Of note as well is the significant negative effects of internet use on loan terms for formal borrowing that can also be seen as supportive for our informational overload coupled with financial and digital literacy arguments in that rural borrowers may have uninformed applications with unrealistic term expectations (Bruhn and Love, 2014; Levine, 2005a).

#### Table 7

Alternative measure of rural access to finance - Loan amount.

	Heteroscedasticity-based instruments
	Loan Amount
Internet use	-1.1084**
	(0.5130)
Age of household head	-0.0494***
	(0.0034)
Household head can read or write	-0.0467
	(0.1392)
Household head is female	-0.1253
	(0.0930)
Size of household	0.1817***
	(0.0224)
Dependency ratio	-0.1053**
	(0.0447)
Member of socio-political organization	-0.5194***
	(0.0913)
Total land of household	0.003
	(0.0022)
Average years of schooling	0.0854***
	(0.0223)
Suffer from an unexpected loss	0.9396***
-	(0.0933)
Number of businesses	0.0556
	(0.0699)
Log of monthly wages	0.0682***
	(0.0159)
Log of total asset values	0.4649***
-	(0.0594)
Distance to VBARD / BAAC travel time	0.0068
	(0.0079)
Distance to VBSP / Agric Coop. travel time	0.0085
	(0.0074)
Distance to Credit organization/GCB travel time	0.0032
-	(0.0054)
Distance to other commercial banks	0.0086**
	(0.0038)
No. of observations	7630
Under identification test	0
Over identification test	0.4033
Weak identification test	26.7653

*Notes*: Robust standard errors in parentheses. The under-identification test is an LM test based on Kleibergen and Paap (2006) rk LM statistics with the null hypothesis that the model is under identified. The over identification test is based on the Hansen J test with the null hypothesis that all instruments are valid. For weak identification, Cragg–Donald Wald F statistics are reported. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

#### 6. Robustness checks

6.1. Alternative measure for credit access: loan amount

We estimate our core model as represented by Eq. (1) with an alternative measure of our dependent variable as a test of sensitivity of our estimation outputs. In line with the extent development literature (Kara et al., 2021; Menkhoff et al., 2012) we use the value of approved loans – Loan Amount – as our alternative measure of rural access to credit. Whilst our use of loan approval as our original dependent variable is a truer measure of rural access to credit as it measures access via a likelihood function, our use of the value of approved loans as an alternative dependent variable does also capture similar dynamics albeit with a greater focus on the value. Both measures – likelihood of loan approval and value of approved loan - are valid indicators of rural access to credit given that they focus on exogenous borrowing constraints rather than credit program participation or credit uptakes (Hazarika and Alwang, 2005; Swaminathan et al., 2010). Consistent with our core estimations - panel A, Table 5 – the results of our alternative measure of access to credit are indicative of technology as a negative predictor of the value of approved loans. Once again, this model is run using the Lewbel (2013) methodology with heteroskedastic-robust standard errors, and panel fixed effects for both cross-section and period. Our results in Table 7 with our alternative measure of rural access to finance serve to indicate the robustness of our core estimation outputs.

## 6.2. Alternative estimation methods: Propensity Score Matching with Difference-in-Difference

In order to enhance the reliability of our findings, we implement multiple estimation techniques to tackle the problem of endogeneity. We utilised a combination of Propensity Score Matching (PSM) and Difference-in-Differences (DiD) analysis to estimate the Average Treatment Effect on the Treated (ATT).

The introduction of Propensity Score Matching as a method to address selection bias is a crucial development in observational studies (Lee, 2016; Zaefarian et al., 2017). PSM is one of the methods used to account for potential selection bias, alongside instrumental variables (Pizer, 2009). The use of PSM should be guided by a thorough understanding of data properties and their implications for theory, measurement, and modelling (Neumann and Graeff, 2015).

Although PSM is not a direct method to address endogeneity, it can help mitigate selection bias by matching treated and control groups on observable characteristics. If part of the endogeneity problem stems from selection bias into internet use, PSM could be a supplementary analysis. However, PSM does not inherently address endogeneity due to omitted variables that affect both treatment and outcome. This approach enabled us to address any potential selection bias and ascertain the causal influence of internet usage on financial access with greater assurance. In particular, we matched individuals who utilised the internet with those who did not, based on a range of observable variables such as household characteristics which were expected to affect both their internet use and financial indicators. After identifying treated and control groups, DiD analysis is applied to produce the Average Treatment Effect on the Treated (ATT). Table 8 reports the outputs of propensity score matching, using kernel and nearest-neighbour matching methods. The results, illustrated in Table 8 using both kernel and nearest-neighbour matching techniques, indicate predominantly negative and significant effects for several variables of interest.

In short, the primary analysis of our study revealed statistically significant, negative impacts of internet use on financial access and terms, a finding corroborated by the direction of effects observed in our robustness checks. These results of our tests for robustness underscore our use of the heteroscedasticity-based instrumental variable (IV) method developed by Lewbel (2012) as appropriate for our examination of technology and its impact on rural access to finance as it effectively accounts for endogeneity thus solidifying the credibility of our findings.

# 7. Concluding remarks

Given the advent of digital transformation of our economic system, we set out to better understand the impact of technology on augmenting access to finance. Existing research has shown that interventions that promote greater access to finance are pro-growth and that there is robust evidence of an access to credit and welfare nexus. Given the focus of much of the extant literature on more developed nations with established digital and technological infrastructure, as well as the lack of multi-country analyses, we concentrate our analysis within rural settings of two developing countries, i.e., Vietnam and Thailand where technology inception is still rudimentary. Both nations afford a useful backdrop for investigation and viable scopes of comparative interests given the

# Table 8

Propensity Score Matching with Difference-in-Difference.

	Loan Approve	Loan Amount	Interest rates	Loan Maturity
	Propensity score matchi	ing (PSM)		
Kernel matching	-0.0527**	-0.3917**	-0.3811	-1.4949*
	(0.025)	(0.1949)	(0.2745)	(0.8264)
Nearest-neighbour matching	-0.0492**	-0.3552*	-0.2994	-1.0144
	(0.0248)	(0.2005)	(0.2646)	(0.7721)

*Notes*: Standard error in parenthesis; Nearest-neighbour matching: with replacement, five nearest neighbour matching; Both household head and household characteristics are used in PSM and DiD. \*\*\* p<.01, \*\* p<.05, \* p<.1

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accelerated levels of technological penetration coupled with persistent difficulties of access to credit by the households of rural villages.

Adopting internet usage as our independent measure of technological penetration, we use household-level survey data established from a long-standing research project funded by the Deutsche Forchungsgemeinschaft (DFG) - Thailand Vietnam Socio Economic Panel (TVSEP) – over the period of 2016 and 2017 for our empirical estimations. The dataset comprises of over 4400 rural households within 440 villages across six provinces in Thailand and Vietnam. Implementing a heteroskedasticity-based instrumental variable (IV) method developed by Lewbel (2012) for endogeneity-robust estimates, our results are indicative of a significant negative relationship between technology access as measured by internet use and rural access to finance. Our findings run contrary to the a priori development economic conceptions of the technology and access to finance nexus. We draw from the existing credit demand and informational theory literature for an explanation of technology as a negative predictor of rural access to finance and content that this relationship is borne from excessive informational loads causing distortions in the household expectations of credit availability (Bruhn and Love, 2014). It is also possible to contend that this misalignment in expectations between borrowers and lenders leads to further increases in information asymmetry widening the negative relationship between technology and rural access to credit (Lin et al., 2012). With our dataset we are able to further delineate our estimations along a country-level and type of borrowing to provide richer insight into our baseline results. These additional analyses highlight that the significant negative relationship persists only for Vietnam and also only for informal rural Vietnamese loans. We argue that country level-differences in estimation outputs could be a result of different sovereign levels of economic development. With regards to our findings of technology as a negative predictor of the likelihood of receiving a formal rural Vietnamese loan, we contend that the confluence of technology as proxied by internet access and rural access to finance has augmented the demand-side perceptions and expectations of what options are available. It is possible that there is a mismatch between expectations of rural households between formal and informal lending options (Mora-Rivera and García-Mora, 2021). However, both these elements are opportunities for further examination with possible avenues including the digital divide between rural and urban communities, financial literacy, and socio-economic patterns of borrowing. Our estimations are robust to multiple methods of propensity score matching including Kernel and nearest-neighbour implementations.

Our results allow us to make the following contributions to the extant development literature, especially with a focus on technology inception with emerging market rural settings (Abdulqadir and Asongu, 2022; N'dri and Kakinaka, 2020). Firstly, we extend the existing knowledge in contending that within rural settings, increased internet usage results in greater information asymmetry proliferation, resulting in potentially uninformed and unrealistic loan-based applications. It is also possible that these information asymmetries are exacerbated by trust-based issues with lending sources. These contentions are somewhat supported by our estimation outputs where there are significant negative effects of internet use on access to finance, this is mainly concentrated within the formal sources of borrowing. Additionally, whilst we find no significant effects of internet usage and the likelihood of receiving informal loans, we do observe negative effects on the informal rural loan terms. Secondly, we are also able to contribute to the extant literature in indicating that access to technology as measured by internet use has no impact on Thailand at a country level confirming the presence of sovereign developmental characteristics present in technology-augmented finance. Moreover, our results of negative effects of likelihood of formal loan could also be suggestive that policies promoting greater access to finance are somewhat independent of technological penetration.

Given our findings, we are mindful of further avenues of study. Most notably is further decomposition of both demand- and supplyside dimensions in relation to the informal loan sector and its impact on access to finance given the continual drive towards economic digitalisation. Our data has demonstrated a reduction in the number of informal to formal loans. We are also able to make policy implications in indicating, to an extent, to leaders that there is a need to manage the implications of increased technological penetration especially in relation to financial and digital literacy to mitigate issues of information asymmetries pervasive in rural settings.

## **Declarations of interest**

none

## CRediT authorship contribution statement

**Chung Phan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Stefano Filomeni:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Seng Kiong Kok:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Seng Kiong Kok:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

## **Data Availability**

The authors do not have permission to share data.

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