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Exogenous Crises and Technology Adoption: Evidence from the Effect of COVID-19 on FinTech Adoption

Master's Thesis

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Year of the defence: 2023

Declaration

1. I hereby declare that I have compiled this thesis using the listed literature and resources only.

2. I hereby declare that my thesis has not been used to gain any other academic title.

3. I fully agree to my work being used for study and scientific purposes.

In Prague on 01/08/2023

Tao He

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Abstract

Can exogenous crises affect technology adoption, and if so, how? In this thesis, I study whether a public health crisis, the COVID-19 pandemic, could affect individuals' adoption of financial technology. I combine the health shock of the pandemic and governments' policy responses to measure a country's intensity of exposure to COVID-19. I employ an instrumental variable strategy, using the number of airports and the time of the first confirmed COVID case, to instrument the pandemic exposure intensity in a country. Additionally, I use the difference-in-difference approach to identify the causal effect of the pandemic exposure and I combine the IV and DiD approaches for further identification. The results reveal that a higher intensity of exposure to the pandemic has positive effects on fintech adoption. These effects on fintech adoption can be attributed to increased concerns and distress among individuals about the pandemic situation, which motivate them to adopt financial technologies. The findings of this thesis provide valuable insights into the impact of COVID-19 on society and shed light on the technology adoption process within the context of a public health crisis.[1]

Keywords: Technology Adoption, COVID-19 Pandemic, Financial Technology

JEL Codes: I18, O14, O16, O33

[1]Parts of this thesis have been previously submitted to CERGE-EI as a part of my study (*Academic Writing* and *US Economic History*) on the MAER program.

Abstrakt

Mohou exogenní krize ovlivnit přijetí technologií, a pokud ano, jak? V této diplomové práci studuji, zda by krize v oblasti veřejného zdraví, pandemie COVID-19, mohla ovlivnit adopci finančních technologií jednotlivci. Kombinuji zdravotní šok pandemie a politické reakce vlád k měření intenzity vystavení země COVID-19. Používám strategii instrumentálních proměnných (IV) využívající počet letišť a čas prvního potvrzeného případu COVID k měření intenzity pandemické expozice v dané zemi. Navíc používám k identifikaci kauzálního účinku expozice pandemie metodu difference-in-difference (DiD). Přitom kombinuji IV a DiD přístupy pro další identifikaci. Výsledky ukazují, že vyšší intenzita expozice pandemii má pozitivní vliv na přijetí finančních technologií. Tyto účinky na přijetí finančních technologií lze připsat zvýšeným obavám a strachu jednotlivců z pandemické situace, která je motivuje k přijetí finančních technologií. Výsledky této práce poskytují cenné poznatky dopadu COVID-19 na společnost a objasňuje proces přijetí technologie v kontextu krize v oblasti veřejného zdraví.

Klíčová slova: Adopce technologií, Pandemie COVID-19, Finanční technologie

JEL kódy: I18, O14, O16, O33

Contents

1 Introduction

The role of technology transformation holds significant importance in the process of development. Disparities in technology levels among nations directly impact variations in their economic progress. Less affluent countries have the potential to accelerate their economic growth and narrow the development gap with wealthier nations by embracing more advanced and productive technologies commonly used in developed countries (Nelson and Phelps, 1966). One notable example lies in the adoption of innovative agricultural technologies, which serves as a crucial solution for alleviating poverty in developing countries (Foster and Rosenzweig, 2010). However, the adoption of certain novel technologies, despite their enhanced efficiency and societal benefits, often occurs at a gradual and sluggish pace (Rosenberg, 1972). Consequently, understanding the factors that influence technology adoption becomes highly meaningful, as it enables the prediction of adoption patterns and facilitates the uptake of beneficial technologies.

Researchers have conducted extensive studies to examine the factors that either facilitate or impede the process of technology adoption. Cross-country studies have revealed a correlation between a nation's technology adoption patterns and its level of economic development, human capital accumulation, availability of complementary production resources, as well as the presence of supportive social, legal, and political institutions, international trade openness, and industry structure (Rosenberg, 1972; Comin and Hobijn, 2004; Caselli and Coleman, 2001). Conversely, within-country studies investigated by economists have identified several influential factors at the individual level, such as the expected returns related to benefits and costs, perceived technology value, peer influence, personal and social learning, technological externalities, access to education and training, credit constraints, risk and inadequate insurance coverage, and behavioral norms (Oster and Thornton, 2012; Conley and Udry, 2010; Bandiera and Rasul, 2006; Suri, 2011; Foster and Rosenzweig, 2010). These factors collectively shape individuals' technology adoption decisions within developing countries.

In addition to the above factors within the economic system, external factors can also exert significant effects on the technology adoption process. One such influential factor is the occurrence of diseases and epidemics. Historical evidence, as demonstrated by Pelham

(2017), illustrates that outbreaks such as the Black Death led to substantial population losses, which in turn compelled the adoption of labor-saving technologies in the milling industry in England. Similarly, in the contemporary context, the COVID-19 pandemic has dramatically altered individuals' daily lives and production activities due to its high infection rate. For instance, the closure of schools and universities during the pandemic necessitated the adoption of online classes and educational applications as substitutes for traditional forms of education. Video medical consultation technologies have also played a crucial role in enabling doctors to take medical examinations and provide treatment remotely. Furthermore, to maintain productivity amidst workplace closures, workers have relied on video conferencing tools and team collaboration platforms. The profound impacts of the COVID-19 pandemic on social life make it a compelling case study for examining how an exogenous crisis can influence the technology adoption process.

This thesis examines the adoption of financial technology, commonly referred to as 'fintech', during the COVID-19 pandemic. Selecting fintech to analyze the impact of the public health crisis on technology adoption is motivated by two considerations. Firstly, fintech exerts a substantial influence on economic development and financial inclusion, particularly in developing countries. Tok and Heng (2022) highlights that fintech demonstrates a stronger positive correlation with digital financial inclusion compared to traditional measures, and increased utilization of fintech significantly contributes to bridging the divide between different socioeconomic groups, thereby empowering marginalized populations. Furthermore, financial inclusion is positively associated with growth in GDP per capita, revealing that digital financial inclusion acts as a fundamental driver of economic prosperity (Khera et al., 2021). Secondly, financial technology possesses a longer developmental history compared to online education and telemedicine, resulting in the availability of more abundant and systematic data. Fintech's evolution, starting from the introduction of credit cards and ATMs in the 1950s to the emergence of online banking, mobile payments, peer-to-peer lending platforms, and cryptocurrencies, has provided the public with a deeper understanding of these technologies and facilitated a gradual process of adoption.

The main research question addressed in this paper is how an external public health crisis, specifically the COVID-19 pandemic, causally influences patterns of fintech adoption across different countries. To investigate this question, this study employs a combination of fintech adoption data derived from the Global Findex Database and COVID-19 pandemic data for each respective country. The intensity of exposure to the COVID-19 pandemic in a given country, serving as the independent variable, is measured by considering two key aspects: medical health factors and government policy responses. Furthermore, this paper considers fintech adoption, acting as the outcome variable, by focusing on changes in both the access to fintech and the daily use of fintech between the years 2021 and 2017.

To estimate the effects of the COVID-19 pandemic exposure on fintech adoption, I regress fintech adoption levels on the exposure intensity using simple linear regression, controlling for countries' characteristics. However, it is important to acknowledge certain econometric concerns that may hinder the identification of a causal relationship. For instance, measurement errors in capturing the exposure intensity and the possibility of omitted unobservable variables could pose challenges. To mitigate these potential concerns, I employ an instrumental variable (IV) strategy. In this study, I use the number of airports and the time of the first confirmed COVID-19 case as instrumental variables to capture the intensity of pandemic exposure in a country. This choice is based on the assumption that airport transportation and the timing of the first COVID-19 case are not directly related to individuals' adoption behaviors regarding financial technology, but rather they influence adoption indirectly through their impacts on pandemic exposure. By using these instruments, this study aims to strengthen the identification of the causal relationship between COVID-19 exposure intensity and fintech adoption. Considering the possible problem of weak IV, this paper uses four rounds of Global Findex Surveys to compare pre-COVID-19 and post-COVID-19 fintech adoption levels between highly-exposed and lower-exposed countries using the difference-in-difference (DiD) approach. To address the concern of measurement errors in high-pandemic-affectedness treatment, I use the predicted pandemic exposure intensity obtained from the IV first-stage estimation and employ the IV-DiD approach to re-estimate the causal effects of the public health shock.

The results suggest that higher pandemic exposure intensity has larger effects on financial technology adoption in the short run. For fintech access, countries that experienced more intensive exposure to COVID-19 witness a higher increase in financial account ownership, mobile money account ownership, and debit and credit card ownership. For the daily use of fintech, a higher intensity of exposure to COVID-19 caused an increase in use of debit and credit cards, mobile money, and digital payments. Overall, one unit of increase in exposure intensity could induce around a 20 percentage point jump in adopting financial technologies (both in access and daily use). The DiD and IV-DiD approaches show that treated (highly-pandemic-exposed) or predicted treated countries on average experience a 5 percent greater increase in fintech adoption than control (lower-pandemic-exposed) or predicted control countries, controlling for country characteristics.

In a series of robustness tests, I show that these results are robust for using different outcome variables or changing the sample size. Specifically, apart from using the individuals' daily use of financial card, mobile money and digital payment, I also consider people's initial adoption of digital payment in their daily life directly related to the COVID-19 pandemic to check whether the positive effects of the pandemic exposure intensity on fintech adoption still exist. Moreover, I choose to use a subsample of developing countries to re-estimate the effect of the intensity of exposure to COVID-19 on the changes in fintech adoption among this subsample to check the changes in estimation effects. Furthermore, instead of using the difference in fintech adoption between 2021 and 2017, I use the difference between 2021 and 2014 for fintech access and daily use as the alternative dependent variables to check whether there are similar positive effects for fintech adoption. The main results are robust to the alternative outcome variables and different sample sizes.

Regarding the mechanism behind the observed positive effects of exposure intensity on fintech adoption, I posit that higher intensity of exposure to COVID-19 in a country leads to increased concerns and distress among individuals about the pandemic situation. Consequently, individuals are more inclined to adopt financial technologies as a solution to mitigate infection risks and avoid the various policy restrictions imposed during the pandemic. To assess this proposed mechanism, I use the Google search trend for the term 'COVID' as a proxy to measure the level of stress and concerns related to the pandemic across different countries. The estimation results confirm the existence of this channel, thereby providing empirical evidence that supports the notion that increased exposure intensity to the pandemic drives financial technology adoption as individuals seek ways to address their concerns and adapt to the challenges imposed by the ongoing crisis.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature studying the factors of technology adoption. This is followed by introducing data sources and main variables in Section 3. Section 4 develops the empirical identification strategy. Section 5 reports the main results of the effect of exposure intensity on fintech adoption. A series of robustness checks are undertaken in Section 6. Section 7 further explores the mechanism behind the causal relationship between exposure intensity and fintech adoption. Finally, Section 7 concludes.

2 Literature Review

In this section, I review the existing research investigating factors that affect technology adoption. According to current studies, there are many factors from the economic system, such as net returns and human capital accumulation, that affect the adoption and diffusion process of new technology. There is relatively less literature on how factors outside of the economic system, such as an exogenous crisis, affect technology adoption.

2.1 Cross-country Technology Adoption

Rosenberg (1972) provides an early exploration into the factors affecting technology adoption. He finds that in spite of the appearance of some inventions with high technological novelty, the adoption and diffusion of such novel technologies are much more gradual and slower than expected. He attempts to unravel the intricate interconnections between the technical and economic realms of discourse. He considers that the inherent imperfections of new technologies impede the widespread adoption of novel products, necessitating a gradual process to surmount these limitations. Furthermore, the advancement of innovations also requires the acquisition of specialized human skills, which, in turn, demands a considerable investment of time. Moreover, the complementarity between various factors in the production process, such as capital, contributes to the sluggish adoption of new technologies because of production factors' constraints. Despite the potential productivity gains generated by new technologies' adoption, the continuous improvements of 'old' technology could postpone its time of exclusion from production. Technology adoption occurs within a specific context where the institutional backdrop encompassing social, legal, and political factors significantly influences the adoption process. Rosenberg's (1972) arguments provide a comprehensive framework for systematically understanding the adoption and diffusion of new technology. However, his analysis predominantly concentrates on the supply-side factors that influence adoption and diffusion. Although empirical evidence is not explicitly provided, his theoretical framework acts as a guiding foundation for subsequent studies to formulate and test more precise hypotheses regarding the cross-country spread of new technologies.

Comin and Hobijn (2004) document cross-country technology adoption patterns by leveraging a historical dataset from 23 industrialized economies and spanning over 200 years, comprising 25 major technologies. They use this panel data to identify the determinants influencing the pace of technology adoption and its diffusion across countries. They regress the country-level technology adoption measure on a technology-specific time dummy and a series of covariates to identify the pivotal factors shaping cross-country variations in technology adoption rates. Their findings underscore the significant roles of human capital and income per capita in driving technology adoption. Furthermore, they highlight that an effective legislative framework and an open-trade economy could mitigate opposition and protectionist forces, therefore, foster the uptake of new technologies. Comin and Hobijn (2004) also document that the pre-World War II era witnessed the salience of administrative structures and regime types, while post-war dynamics showcased a remarkable acceleration in the transmission of technologies from leaders to followers. This accelerated process is attributed to the convergence of crucial determinants of technology adoption, such as human capital accumulation. Importantly, the authors' analysis focuses primarily on horizontal cross-country disparities in technology adoption, thus overlooking the temporal evolution of the average adoption rate over time.

Caselli and Coleman (2001) identify factors that predict the adoption of computers across countries using the case of the diffusion of computer technology worldwide. They use detailed panel data on imports of computer equipment for all countries from 1970 to 1990 to characterize the determinants of computer imports. They regress computer imports per worker on a set of explanatory variables, controlling for a set of year dummies and country fixed effects. Their findings show the positive correlation between computer adoption and high levels of human capital as well as a robust manufacturing trade openness. Moreover, good property rights protection, high rates of investment per worker, and a small share of agriculture in GDP contribute to the facilitation of computer adoption.

There is also some evidence for a negative role of the size of government and a positive impact of the share of manufacturing in GDP. Although they identify some possible determinants that affect the adoption of computers, it is important to note that this study falls short of establishing a convincing causal relationship between these factors and technology adoption. Furthermore, it does not encompass all crucial factors, such as learning externalities, which are essential in understanding the dynamics of computer adoption.

2.2 Within-country Technology Adoption

Oster and Thornton (2012) collect data from a randomized experiment involving the distribution of menstrual cups in Nepal to investigate the role of product value and peer influence in the adoption of new technology. They estimate the importance of cup value (benefits and costs) and find girls with a greater need for mobility and those relying on time-consuming existing technologies are more inclined to adopt menstrual cups, and thus cost and benefit factors do induce usage. Furthermore, they explore the impacts of peers in driving adoption, finding that the effects of peers are large and that strong friendships are more prominent than weak friendships in driving adoption. While the effects of cup value exhibit relative consistency over time, peer effects display notable variations throughout the sample period. Oster and Thornton (2012) also attempt to identify the mechanisms behind the peer effects on the adoption of menstrual cups, proposing three potential channels: individuals imitate their friends, learn about the benefits of technology from their peers, or acquire knowledge on using new technology through their social circles. The findings indicate that friends play a crucial role in facilitating the learning process for cup usage, although this effect diminishes over time. However, there is no evidence suggesting that peer exposure directly influences the desire to use the new product. The authors claim that for easy-to-use products, there is only a limited argument for the success-at-usage mechanism, but they are unable to distinguish between the two explanations of either imitation or learn-about-value.

Conley and Udry (2010) use individual-level data to investigate the role of social learning on agricultural technology adoption in Ghana. In the 1990s, an established maize and cassava production system in Ghana was transformed into intensive production of pineapples for exports. This transformation in the farming system involved the adoption of a set of new technologies, such as fertilizer and other agricultural chemicals. To define information links and measure the extent of social learning, they gather detailed information on whom individuals know and talk to about farming. They also incorporate geographic, soil, credit, and family relationship information to control for confounding factors to address concerns of correlated unobservables. Their strategy for identifying social learning's effects relies on using the specific timing of plantings to capture opportunities for information transmission. Staggered planting generates a sequence of dates when new bits of information may be revealed to each farmer. They isolate instances of new productivity information revealed to the farmer by conditioning upon measures of growing conditions. Then they examine whether the new information is associated with a farmer's fertilizer use in a manner according to the nature of social learning assumptions. They test the effects of social learning by estimating how farmers' input decisions (fertilizer usage) adjust in response to the actions and outcomes of other farmers in their information network. The findings reveal significant effects of input productivity news from a farmer's information neighborhood on their input use decisions.

Similarly, Bandiera and Rasul (2006) also analyze how social learning could affect a farmer's initial decision to adopt a new agricultural technology using the case of adopting a new crop, sunflower, by farmers in Northern Mozambique. They use the number of adopters among a farmer's self-reported network of family and friends to measure the available information on sunflower cultivation from his social network. Accordingly, farmers who have more social ties are more likely to exchange information and learn from others. To identify the effect of social learning on sunflower adoption, they estimate farmers' propensity to adopt sunflowers as a function of the number of adopters among their social networks. They find that there is an inverse U-shape relationship between the probability of adoption and the number of adopters in the network. The marginal effect of an additional adopter among friends and family is positive when there are few adopters but turns negative when there are many. They also show that the network's effects vary across farmers' initial information on sunflower cultivation. The relationship between adoption propensity and the number of adopters in the network is weaker for farmers who possess more extensive prior knowledge. Therefore, they claim that in an environment where information barriers impede new technology adoption, individuals would learn such information from existing adopters within the network. Moreover, social effects on technology adoption are heterogeneous. They consider social learning as the mechanism connecting adoption decisions with social networks in their rural Northern Mozambique setting. However, there are other possible channels to explain the effects of social networks, such as risk sharing within the network, which the authors do not address.

Suri (2011) finds that improved agricultural technologies are not universally adopted and low adoption rates persist for a long time. He investigates this technology adoption puzzle in developing countries, namely, there are low adoption rates of agricultural technologies that could potentially increase average farm profits significantly. He proposes an explanation that the benefits and costs of adopting technologies are heterogeneous and thus farmers with low net returns do not adopt new technologies. He examines this hypothesis by using a panel dataset on maize cultivation in Kenya from 1996 to 2004. He identifies the distribution of returns to adopting hybrid maize and estimates the correlated random coefficient structure of the yield functions. By constructing counterfactual distributions of returns for all farmers in the sample, he uncovers strong evidence of heterogeneity in the returns to the hybrid maize adoption. The returns distribution reveals that farmers with the highest estimated gross returns also face the greatest costs associated with acquiring the technology (poor access to input suppliers caused by poor infrastructure). Some farmers with lower returns still adopt the technology, while others with zero returns intermittently switch between adoption and non-adoption in response to various shocks. Consequently, farmers with high net returns to the technology are more likely to adopt it, while those with low returns choose not to. Thus, the persistent lack of adoption can be attributed to the distribution of observable and unobservable costs and benefits associated with technology adoption. In this context, households' adoption decisions are influenced by heterogeneous costs and benefits, and the observed and unobserved variation in net benefits to the technology makes their adoption decisions rational.

Foster and Rosenzweig (2010) review micro-level studies of new agricultural technologies' adoption process to investigate the barriers to technology adoption in low-income countries. Overall, they consider that factors affecting decisions on technology adoptions include the financial and non-financial returns to adoption, one's own learning and social learning, technological externalities, scale economies, schooling, credit constraints, risk and incomplete insurance, and departures from behavioural rules. Specifically, technology profitability is the key factor for profit-maximizing entities, and new technologies are also adopted for agents' utility maximization. In an environment where new technology is introduced, new information affects individuals' adoption behaviour, and learning is important in this process. The impact of learning is affected by the complexity of new technology and technological returns vary with individual attributes. In an information-learning setting, individuals learn about the overall profitability of new technology and compare this to the returns of the existing technology. Moreover, individuals could learn from others, and it could facilitate more knowledge acquisition than only learning from their own experience. Given the fixed costs associated with technology adoption and the riskiness of returns, imperfections in credit and insurance markets may result in wealthier or more financially stable individuals being more inclined to adopt new technologies. Consequently, the variation in profitability poses challenges in accurately assessing the true returns and profitability of new technology, while credit market imperfections restrict access to capital and hinder the realization of gains for individuals with limited funds.

2.3 COVID-19 and Technology Adoption

The preceding subsections provide a comprehensive overview of studies examining technology adoption across countries and within a particular country, focusing predominantly on endogenous factors within the economic system. In contrast to these studies, I study the impact of an 'exogenous' crisis, outside of the economic system, on the technology adoption process, namely the COVID-19 pandemic. There are some papers attempting to investigate the technology adoption process during the COVID-19 pandemic.

Valero and Reenen (2021) investigate the impact of the pandemic on technology adoption and its implications for future productivity in the United Kingdom. Prior to COVID-19, the UK has already faced a productivity crisis, partially attributed to limited technology adoption. According to the authors, while mainstream economic theory predicted a slowdown in technology adoption due to decreased demand, increased uncertainty and liquidity shocks, empirical evidence suggests that the public health crisis actually accelerated technology adoption. Riom and Valero (2020) find that over 60% of firms responded to the pandemic by adopting new technologies or management practices, with a third of them investing in digital capabilities. These short-term responses are expected to have lasting effects and improve firms' technological trajectory. However, the pandemic also introduces new risks to innovation, particularly for financially constrained firms, potentially leading to reduced investment in innovation. Additionally, according to Valero and Reenen (2021), the pandemic is shaping the direction of innovation, with a notable increase in research and development focused on areas relevant to the pandemic, such as video conferencing and telecommuting.

Passarelli et al. (2023) explore the factors influencing the adoption of new technologies by agricultural entrepreneurs in Italian rural areas during the COVID-19 pandemic. Their proposed theoretical framework considers variables such as behavioural attitude, subjective norm, perceived behavioural control, information and knowledge acquisition, and access to external financial resources. They use a questionnaire to collect data on demographic information and technology adoption factors from 130 Italian agricultural enterprises. To understand adoption-influential factors, they use the binary logistic model with the dependent variable 'intention to adopt'. The empirical results show positive effects of behavioural attitude to environmental and economic sustainability on the intention to adopt new technologies. Moreover, planned behavioural control exerts a positive impact on the willingness to embrace new technologies. However, the authors find that information and knowledge acquisition and access to external financial resources are not significant for the intention of agricultural entrepreneurs to adopt new technologies.

Two papers provide specific insights into the adoption of financial technologies during the COVID-19 pandemic. Fu and Mishra (2022) study the effects of the COVID-19 pandemic on fintech adoption across countries and investigate how the pandemic affected the financial market structure. To measure fintech adoption, they extract daily information on all finance category mobile application downloads from 2019 to 2020 for all countries available in the AppTweak platform. Their primary explanatory variables are proxies for the spread of COVID-19 and related government policies. Their empirical methodology employs panel data regression models to estimate the change in fintech app adoption between pre- and post-COVID-19. To address spatial and temporal trends, they account for country-or app-level characteristics and seasonality. The findings reveal significant increases in the adoption of finance-related mobile applications in terms of both relative and absolute per capita measures, driven by the spread of the pandemic and government-imposed lockdowns. Moreover, traditional incumbents initially experienced substantial growth in their digital offerings due to customers' existing familiarity. However, over the course of time, 'BigTech' companies and emerging fintech providers leverage their competitive advantages and network effects to outperform traditional incumbents.

Saka et al. (2022) study whether epidemic exposures cause a shift in fintech usage and if so, which group is mainly involved in this shift. They use global epidemics data and match Global Findex surveys for some 250,000 individuals in 140 countries with Gallup World Polls to gather individuals' adoption behaviours and socioeconomic backgrounds. They employ a linear probability model with a difference-in-differences specification to infer the causal effect of epidemic exposure on an individual's usage of digital and traditional financial services. The results indicate that past epidemic exposures are associated with an increase in online and mobile banking and a reduction in financial services via brick-and-mortar branches. Moreover, these effects manifest primarily in the short term rather than persisting over a long period. Furthermore, there are heterogeneous treatment effects in the adoption process. Mainly young high earners with full-time employment would take up online and mobile transactions in response to epidemics.

In this paper, I contribute to the existing literature by addressing a notable gap in previous research. While some studies have acknowledged the impact of epidemics on financial technologies, only a few have attempted to establish a causal relationship between epidemic exposure and fintech adoption, and even fewer have explored the underlying mechanisms. In this study, I aim to bridge this gap by leveraging cross-country variation in the intensity of exposure to COVID-19. Using the difference-in-differences (DiD) and instrumental variable (IV) approaches, I identify the causal relationship between pandemic exposure intensity and fintech adoption patterns while also exploring how different exposure intensities could drive varied technology adoption. By doing so, this research provides new insights into understanding how exogenous public health crises could accelerate the technology adoption process.

3 Data

To estimate the effects of the COVID-19 pandemic exposure on fintech adoption, I use several primary datasets to capture a country's financial technology adoption level and COVID-19 affectedness.

3.1 Financial Technology Adoption Data

The first dataset is the Global Findex Database (Demirgüç-Kunt et al., 2022), the most definitive data source to investigate individual access and use of financial services on a global scale, including savings, borrowing, and payment, with four rounds of surveys in 2011, 2014, 2017, and 2021 spread over 123 economies. Moreover, the Global Findex survey in 2021 investigated around 125,000 adults across countries during the COVID-19 pandemic. It also includes some questions about the adoption of digital merchant and utility payments specific to this pandemic.

To identify the fintech adoption level in a country, I measure this variable from two aspects: fintech access and the use of fintech. These two features cover individuals' main connection with financial technologies in their daily life. If they want to utilise commonly adopted financial technologies to obtain financial services, the first step is having access to such technologies. In this paper's setting, I use three variables to measure access to fintech: account ownership, debit and credit card ownership, and mobile money account ownership. To reduce the daily use of cash, individuals first need to have a valid account in a formal financial institution to enable themselves to conduct non-cash transactions. To be more specific, some individuals open accounts in banking institutions and obtain debit or credit cards so that they can take cards with them conveniently and use mobile banking applications. Besides bank cards that are widely used in developed countries and rapidly expanding in developing countries, mobile money[2], a new form of digital finance, is becoming widely popular in developing countries. If individuals have a mobile money account, it allows them to take advantage of this efficient and

[2]Mobile money services operate through a simple SMS message interface on a SIM card to allow the transfer and storage of up to 1,000 US dollars. Mobile money accounts are PIN protected and can only be accessed by account owners, who can withdraw and deposit their money using networks of mobile money agents(Riley, 2022).

convenient microfinance service. Moreover, individuals could obtain various financial services and conduct multiple financial activities after accessing financial technologies from financial service providers. Nowadays, financial services involving the general public include depositing and withdrawing money, transferring between accounts, and making digital payments based on a variety of life scenarios, such as making in-store and online shopping, paying bills for various services, and other common daily financial activities.

I extract some questions (listed below) related to financial account ownership and fintech usage behaviours as dependent variables. These fintech access variables include Account Ownership, Debit or Credit Card Ownership, and Mobile Money Account Ownership. Moreover, these variables about fintech use include Debit or Credit Card Usage, Mobile Money Usage, and Digital Payment Making. Given the variations in baseline fintech adoption levels in different countries, it is challenging to identify and compare cross-country fintech adoption patterns during the COVID-19 pandemic. To address this concern, I use the differences in these indicators between 2021 and 2017 as dependent variables.

The questions from the Global Findex Survey used in this paper are shown below. The questions I use to measure fintech access are as follows:

- The percentage of respondents who report having an account at a bank or other types of financial institutions.
- The percentage of respondents who report having a debit or credit card.
- The percentage of respondents who report having a mobile money account.

The questions I use to measure fintech use are as follows:

- The percentage of respondents who report using a debit or credit card.
- The percentage of respondents who report using a mobile money account two or more times a month.
- The percentage of respondents who report making or receiving a digital payment.
- The percentage of respondents who report using a mobile phone or the internet to pay bills.
- The percentage of respondents who report making a digital in-store merchant

payment.

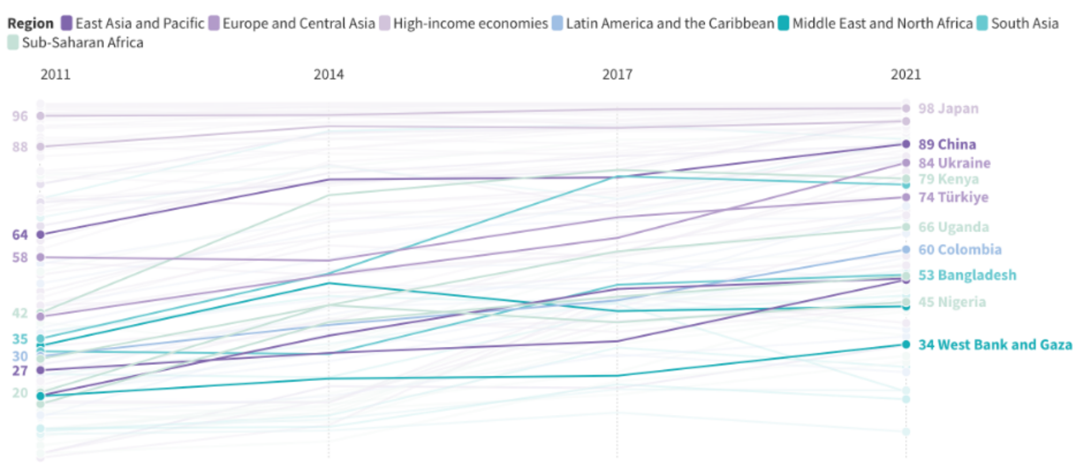
- The percentage of respondents who report making a digital online merchant payment for an online purchase.

- The percentage of respondents who report making a digital merchant payment.

- The percentage of respondents who report making a utility payment using an account.

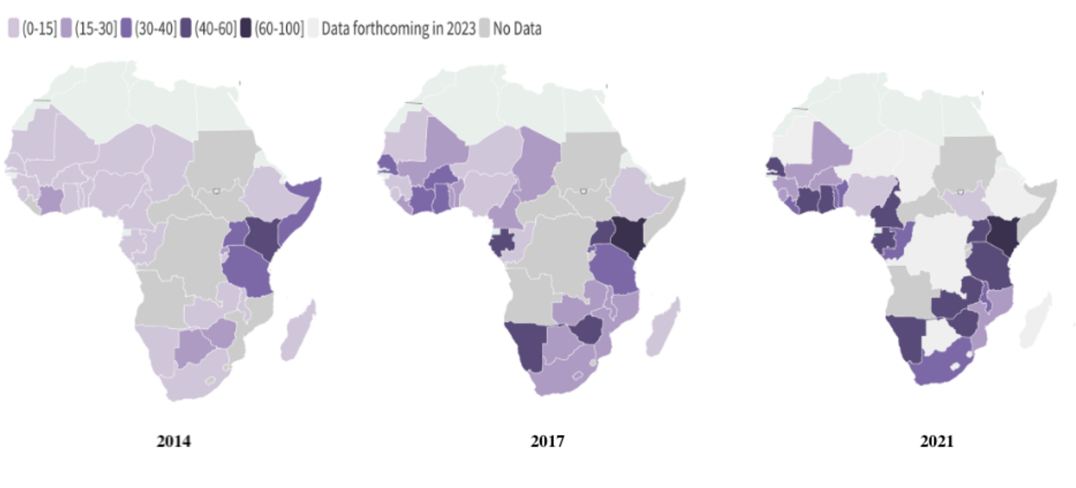
According to the 2021 Global Findex Survey, account ownership is experiencing fast growth in both developed and developing economies (Figure 3.1). In 2011, 51 percent of adults worldwide had an account at a financial institution or through a mobile money provider. However, this proportion reached 76 percent in 2021, and 71 percent of adults in developing economies have account ownership. Although the increase is mainly from China and India, the Sub-Saharan Africa region has witnessed the rapid popularity of mobile money ownership (Figure 3.2). During COVID-19, with the rise in infection rates, Internet and mobile usage have also risen, resulting in the acceleration of digital payments in different forms, especially in developing countries. Lockdown measures and business closures transform individuals from in-person and cash-based payers to digital payers using an account, including direct transfer, bank card, mobile money, or other methods.

Figure 3.1: Adults with an Account across Countries 2011–2021 (in %)



Notes: This figure shows the proportion of the population owning an account at a bank or regulated institution (such as a credit union or microfinance institution) in every single country from 2011 to 2021. *Source:* Global Findex database

Figure 3.2: Adults with a Mobile Money Account across Africa 2014–2021 (in %)



Notes: This figure shows the proportion of the population owning a mobile money account in Sub-Saharan African countries in 2014, 2017, and 2021. In 2021, 33 percent of adults in the Sub-Saharan Africa region had a mobile money account. This number surpassed the global average level of mobile money account ownership, which stood at 10 percent, by more than three times. Furthermore, about three out of four mobile account owners in Sub-Saharan Africa used their mobile money accounts to make or receive payments during the same period. *Source:* Global Findex database

3.2 COVID-19 Affectedness Data

To measure the intensity of exposure to COVID-19 across different countries, I employ multiple data sources. Firstly, I use the Coronavirus Pandemic (COVID-19) dataset from Our World in Data (Mathieu et al., 2020), which provides the coronavirus profiles of 207 countries. COVID-19 is a crisis in the field of public health, and its most direct impact is to endanger the health of the general public. Therefore, the damage to public health is an essential criterion to measure a country's pandemic affectedness. I mainly extract two sections: the confirmed infection cases and the number of deaths caused by COVID-19 in a country in 2021. To realize cross-country comparisons, the absolute numbers of infection and death cases are standardized by each country's population size in 2021 into relative values.

In addition to the impact on public health (infection and even death), a less obvious but equally important and wide-ranging aspect is the government's policy responses to the COVID-19 pandemic. Facing highly infectious COVID-19, to protect the health of the public, governments have to implement a series of pandemic prevention and control policies, such as lockdown and travel restrictions. At the same time, governments also attempt to maintain smooth economic activities and social order. Therefore, governments have to make a trade-off between pandemic prevention and control and economic recovery, and this situation is reflected that governments in different countries implemented pandemic policy responses with various degrees of severity. Although people in some countries did not experience high COVID-19 infection and death rates, they faced severe daily life restrictions imposed by strict pandemic policies, such as China's long-lasting lockdown and quarantine policies. In contrast, although some governments have not implemented harsh pandemic policies to respond to COVID-19, there are high infection rates and even death rates in such countries. For example, the United States experienced the peak of the health impact of COVID-19 in early 2022. Therefore, the separate impact of the COVID-19 pandemic on health cannot effectively describe the pandemic affectedness in a country.

To obtain more comprehensive COVID-19 affectedness profiles across countries, I also measure the stringency of government policy measures to deal with COVID-19. Given that different countries formulate various policies in different areas, a cross-disciplinary team from Oxford University has compiled a dataset that captures the breadth and intensity of government actions worldwide (Hale et al., 2021). This dataset incorporates a stringency index that aggregates policy responses and allows for comparisons between countries. By employing this index, I assess the social impact of COVID-19 through the lens of government policy measures.

Tables 3.1 and 3.2 present the ten countries most and least exposed to the pandemic, respectively, based on exposure intensity scores. Peru emerges as the most heavily pandemic exposed country in the sample, with an intensity score of 0.7133, while Cote d'Ivoire exhibits the least exposure (0.0362). The average exposure intensity across countries is 0.407. These two tables indicate that the Europe and Central Asia region experiences a higher intensity of exposure to COVID-19, and there are eight countries from this region among the ten countries with the highest exposure intensity. In contrast, the Sub-Saharan African region overall undergoes lower pandemic exposure intensity, as six of the ten countries with the lowest exposure intensity are from this region.

Table 3.1: 10 Countries Experiencing the Highest Exposure Intensity in the Sample

Country	Region	Income Group	Development Stage	Pandemic Exposure Intensity
Peru	Latin America and the Caribbean	Upper middle income	Developing	0.7133
Slovak Republic	Europe and Central Asia	High income	Developed	0.6720
Georgia	Europe and Central Asia	Upper middle income	Developing	0.6555
Slovenia	Europe and Central Asia	High income	Developed	0.6208
Czech Republic	Europe and Central Asia	High income	Developed	0.6060
Greece	Europe and Central Asia	High income	Developed	0.5881
Bulgaria	Europe and Central Asia	Upper middle income	Developing	0.5675
Netherlands	Europe and Central Asia	High income	Developed	0.5588
Brazil	Latin America and the Caribbean	Upper middle income	Developing	0.5552
United Kingdom	Europe and Central Asia	High income	Developed	0.5433

Notes: The formula for calculating the intensity of exposure is: exposure intensity = health exposure + policy response. The health exposure is calculated by adding the COVID-19 infection rate and 100 times of death rate together. The policy response is calculated by dividing the COVID-19 policy stringency index by 200 (to make the measurement standardized).

Table 3.2: 10 Countries Experiencing the Lowest Exposure Intensity in the Sample

Country	Region	Income Group	Development Stage	Pandemic Exposure Intensity
Cote d'Ivoire	Sub-Saharan Africa	Lower middle income	Developing	0.0362
Tanzania	Sub-Saharan Africa	Lower middle income	Developing	0.0427
Nicaragua	Latin America and the Caribbean	Lower middle income	Developing	0.0452
Burkina Faso	Sub-Saharan Africa	Low income	Developing	0.0709
Taiwan, China	East Asia and Pacific	High income	Developed	0.1043
Afghanistan	South Asia	Low income	Developing	0.1100
Togo	Sub-Saharan Africa	Low income	Developing	0.1136
Senegal	Sub-Saharan Africa	Lower middle income	Developing	0.1440
Tajikistan	Europe and Central Asia	Lower middle income	Developing	0.1505
Cameroon	Sub-Saharan Africa	Lower middle income	Developing	0.1600

Notes: The pandemic exposure intensity calculation method is mentioned in the *Notes* of Table 3.1.

3.3 Control Data

I also use data from the World Bank to gather the measurement of countries' socioeconomic characteristics, including a country's economic development, population age structure, and internet infrastructure. A country's economic development level is measured by its GDP per capita in constant 2015 US dollars. The population age structure in a specific country is measured with the median age, which could effectively capture the distribution of age groups. Considering there is no direct data to compare Internet infrastructure across countries, I use the percentage of individuals among the population using the Internet to capture individuals' Internet access.

Moreover, to measure a country's governance capacities, I use the Worldwide Governance Indicators (WGI) database of the World Bank (Kaufmann et al., 2011), which provides six governance dimensions for over 200 countries and territories over the period of 1996–2021. I select four dimensions of governance that are more relevant to this paper's setting, including government effectiveness (citizens' appraisals of the caliber of public and civil services, the development and execution of policies, and the trustworthiness of the government's dedication to such policies), regulatory quality (citizens' appraisals of the government's capacity to devise and execute effective policies and regulations to foster the growth of the private sector), the rule of law (citizens' appraisals of the effectiveness of contract enforcement, protection of property rights, and the performance of the police and judiciary), and control of corruption (citizens' perceptions of the degree to which public power is employed for personal benefit or private advantage). Then I calculate each country's governance capacity as the mean of these four governance indicators in 2021. Table 3.3 lists the ten countries with the highest and lowest governance capacity, with the average governance capacity being 0.093. Notably, there is a strong correlation between a country's economic development level and its governance capacity, with developed countries tending to exhibit higher governance capacities.

Table 3.3: 10 Countries with the Highest and Lowest Governance Capacity Separately in the Sample

10 countries have the highest governance capacity				10 countries have the lowest governance capacity			
Country	Income Group	Development Stage	Governance Capacity	Country	Income Group	Development Stage	Governance Capacity
Singapore	High income	Developed	2.138	South Sudan	Low income	Developing	-2.057
Finland	High income	Developed	2.047	Venezuela, RB	Lower middle income	Developing	-1.987
Denmark	High income	Developed	2.029	Afghanistan	Low income	Developing	-1.497
Norway	High income	Developed	1.891	Congo, Rep.	Lower middle income	Developing	-1.354
Switzerland	High income	Developed	1.891	Iraq	Upper middle income	Developing	-1.347
Netherlands	High income	Developed	1.824	Zimbabwe	Lower middle income	Developing	-1.284
Sweden	High income	Developed	1.817	Myanmar	Lower middle income	Developing	-1.256
New Zealand	High income	Developed	1.795	Iran, Islamic Rep.	Lower middle income	Developing	-1.131
Australia	High income	Developed	1.691	Lebanon	Upper middle income	Developing	-1.118
Iceland	High income	Developed	1.680	Nicaragua	Lower middle income	Developing	-1.070

Notes: I calculate governance capacity by adding four governance indicators together and dividing the sum by 4.

4 Empirical Strategy

4.1 Estimation with Simple OLS

To estimate the effect of the intensity of exposure to the COVID-19 pandemic on the adoption of financial technologies, I use the following OLS regression specification:

$$FintechAdoption_c = \beta_0 + \beta_1 ExposureIntensity_c + X_c^{'}\gamma + \varepsilon_c \tag{4.1}$$

where the dependent variable $FintechAdoption_c$ is the fintech adoption level in country c, mainly shown in two aspects: fintech access and the use of fintech. On the right-hand side, $ExposureIntensity_c$ is a composite index constructed by the measures of public health and government policy responses to reflect the intensity of exposure to the pandemic in a country in 2021. Furthermore, I control for a series of country characteristics X_c that might affect the fintech adoption level in a country, including GDP per capita, access to the internet, and population age structure. Firstly, income level in a country has a direct positive impact on fintech adoption. The richer countries would have more developed financial sectors, invest more in the fintech infrastructure, and have more compact fintech development regulation, which could facilitate the domestic adoption of fintech. Secondly, fintech is technologically supported by the internet infrastructure, and higher access to the internet would support digital financial services, which might induce a higher fintech adoption level. Thirdly, existing research (Saka et al., 2022) shows that young people are more likely to adopt the latest financial technologies. Thus, I also consider the population age structure in a country as an essential control variable. ε_c is the error term capturing the unobservables that could affect the financial technology level in a country.

COVID-19 represents an exogenous shock to public health, and its occurrence does not display a correlation with a country's fintech adoption level. Nonetheless, my measurement of COVID-19 exposure intensity incorporates factors such as the percentage of infection and death cases, as well as the stringency of government policies. Firstly, a country's governance capacity influences the accuracy of COVID-related records, with higher-capacity countries exhibiting more precise reporting by their health authorities. Conversely, countries with lower governance capacity may struggle to provide accurate information regarding the domestic spread of COVID-19. For instance, Turkmenistan stands as the only country worldwide that officially reports no COVID-19 cases, despite unofficial media reports indicating the pandemic spread within the country (Hashim et al., 2022). Secondly, varying governance capacities lead governments to adopt different levels of policy stringency in response to COVID-19 transmission. These capacities not only impact the measurement of exposure intensity through policy responses but also affect a country's pandemic prevention and control efficacy, which subsequently influences infection and death rates and therefore the public health aspect of exposure intensity. Furthermore, governance capacities directly influence the development of financial industries, as well as the formulation of policies and regulations pertaining to fintech advancement, both of which impact a country's fintech adoption level. Consequently, governance capacity emerges as a factor influencing both the fintech adoption level and the intensity of COVID-19 exposure. To address this endogeneity concern, I incorporate governance capacity as a control variable within the vector of covariates. As mentioned in the Data Section, the governance capacities of governments across countries are measured using the WGI database.

4.2 Endogeneity Concerns and IV Approach

Although I have attempted to control for observable country characteristics that could affect fintech adoption and exposure intensity, there are still some concerns about the estimation. Firstly, the intensity of exposure to the pandemic in this paper not only captures the impact of the pandemic on public health but also gathers government policy responses in dealing with the pandemic. Therefore, how to perfectly combine these two factors to generate a proper and accurate measurement of the exposure intensity is a challenge, and there may be some measurement errors for the exposure intensity in different countries. Secondly, although I control for the observable level of economic development, internet infrastructure, population age structure, and relatively more abstract but still measurable governance capacity, some factors that are difficult to observe and quantify, such as national culture, social rules, group preference, and some other factors may affect both exposure intensity and fintech adoption in a country. These above situations would cause biased estimates of the effects of the pandemic exposure on fintech adoption.

To mitigate these potential endogeneity concerns, I employ the instrumental variable (IV) strategy. I attempt to find a variable that is related to the exposure intensity (relevance) but cannot affect fintech adoption directly, except by affecting exposure intensity (exogeneity). I select the number of airports in a country as the instrumental variable for the exposure intensity, and this choice is based on two considerations. Firstly, the COVID-19 pandemic, being a contagious disease, has human-to-human transmission features. Moreover, the transnational transmission of this pandemic mainly lies in the transnational flow of the population, and flights are one of the main modes of transportation for transnational population flow. Thus, the number of airports would affect the movement of people across regions and therefore the spread of COVID-19. Secondly, airports, as a means of transportation, primarily cater to long-distance travel and cross-regional transportation of goods, with no direct link to individuals' financial behaviors and their adoption of financial technologies. Although there might be a larger number of airports in more economically developed and effectively governed countries, I have attempted to account for these factors in the regression analysis, thus mitigating this concern to some extent.

In fact, several studies have demonstrated a robust association between airport traffic and COVID-19 transmission. Chokshi et al. (2021) investigate whether proximity to international airports was a predictor of higher infection rates during the early stages of the pandemic in the United States. By analyzing county-level COVID-19 incidence data in the weeks following the initial detection of the virus across all 50 states, they compare the incidence of the pandemic in counties adjacent to US international airports with the rest of the state. They find counties with more international airports emerged as initial hotspots for the transmission of the virus, underscoring the significance of airport proximity in the COVID-19 spread. I gather the number of airports in a country from the World Factbook (https://www.cia.gov/), which mainly compares the total number of airports across countries recognizable from the air.

In addition, I attempt another possible instrumental variable: the time of the first confirmed COVID case in a country. On the one hand, due to the high contagiousness of COVID-19, countries with earlier COVID-positive cases indicate that the country has a longer exposure duration to the pandemic and therefore is more likely to have more severe infections and deaths. Additionally, in countries affected by COVID-19 earlier, the government may also have implemented stricter pandemic prevention policies earlier.

Therefore, the earlier the time of the first confirmed COVID case in a country is, the higher the intensity of exposure to the pandemic in that country might be. On the other hand, the time of the first confirmed COVID case in a country is mainly related to some physical factors influencing the spread of infectious diseases (such as geographical location and population movement), but not directly related to people's fintech adoption behaviours, and its influence on adoption behaviour can only work through the pandemic exposure intensity. Therefore, the variable the time of the first confirmed COVID case in a country satisfies the exclusion restriction condition. This paper measures the time of the first confirmed COVID case in a country by calculating the number of days between 30/05/2020 and the time when the first confirmed COVID case was reported in a country. (I use the date 30/05/2020 because, at that time, almost all the countries in the sample had already reported the pandemic infection cases). Therefore, the earlier a country reported the first positive COVID infection case, the larger the value of the variable the time of the first confirmed COVID case would be.

The empirical specification using the IV strategy is shown below. In the first stage, I regress the intensity of exposure to COVID-19 on two instrumental variables: the number of airports and the time of the first confirmed COVID case, controlling for a series of country characteristics. In the second stage, I regress the fintech adoption measures on the predicted exposure intensity from the first stage to obtain the estimate for the effects of the exposure intensity on technology adoption β_1. The first stage is:

$$ExposureIntensity_c = \theta_0 + \theta_1 Airports_c + \theta_2 FirstCase_c + X_c^{'}\vartheta + \nu_c \tag{4.2}$$

where $Airports_c$ is the number of airports in country c, and $FirstCase_c$ the time of the first confirmed COVID case in country c, ν_c is the error term. In the second stage, I use the predicted pandemic exposure intensity from the first stage as the independent variable to estimate the impact on fintech adoption, the interested coefficient is β_1. The second stage is:

$$FintechAdoption_c = \beta_0 + \beta_1 \widehat{ExposureIntensity}_c + X_c^{'}\gamma + \varepsilon_c \tag{4.3}$$

Table 4.1 reports the estimation results for the first stage. It shows that controlling for country characteristics, the number of airports and the time of the first confirmed

COVID-19 case have statistically significant effects on the pandemic exposure intensity in a country. A larger number of airports means there might be more severe pandemic exposure intensity in a country. Interestingly, countries with an earlier first COVID case are more likely to have lower pandemic exposure intensity, perhaps because countries that experienced the pandemic earlier might have reacted earlier to COVID-19 and effectively reduced the rapid spread of the pandemic.

Table 4.1: Results for the First Stage Estimation Using Two Instruments

	(1) Exposure Intensity	(2) Exposure Intensity	(3) Exposure Intensity
Number of Airports	0.000023*	0.0000301***	0.0000296***
	(0.0000136)	(0.0000102)	(0.0000103)
Time of First Case	.0008358	-0.0024547***	-0.0024302***
	(0.0008097)	(0.0007294)	(0.0007366)
GDP per Capita		-0.000***	-0.000*
		(0.000)	(0.000)
Population Age Structure		0.016***	0.016***
		(0.002)	(0.003)
Internet Access		0.001	0.001
		(0.001)	(0.001)
Governance Capacity			-0.010
			(0.031)
Constant	0.322***	0.089	0.073
	(0.076)	(0.067)	(0.085)
N	120	119	119

Notes: This table shows OLS regression of the pandemic exposure intensity with two instruments and a series of country characteristics. Column (1) presents results without adding any controls, and column (2) adds the country's socioeconomic factors but does not control for a country's governance capacity. Column (3) adds all the control variables, and there are no main changes in estimation results compared with column (2). *** significant at 1%; ** significant at 5%; * significant at 10%.

4.3 Alternative Approach with DiD

Although I use two instrumental variables to exploit the exogenous information in the pandemic exposure intensity to identify the causal effects, it is difficult to find an ideal IV at a global scale. Considering the possible problem of weak IV, I use one alternative identification strategy to explore the causal relationship. The Global Findex Database conducted 4 rounds of surveys in 2011, 2014, 2017, and 2021 in most countries. Therefore, it provides a good panel dataset to allow me to compare pre-treatment and post-treatment fintech adoption levels between treated (highly affected by COVID-19) and control groups (less affected by COVID-19) using the difference-in-difference (DiD) approach. However, considering that I only have one-period data (in 2021) for some outcome variables, the DiD approach can only serve as a supplementary analytical method. To implement a DiD approach and estimate a causal effect, I exploit cross-country variation in the exposure intensity. I divide the country observations in the sample into two groups based on whether their intensity of exposure to COVID-19 is above average level (0.406): treated groups (experiencing high pandemic exposure) and control group (experiencing low pandemic exposure).

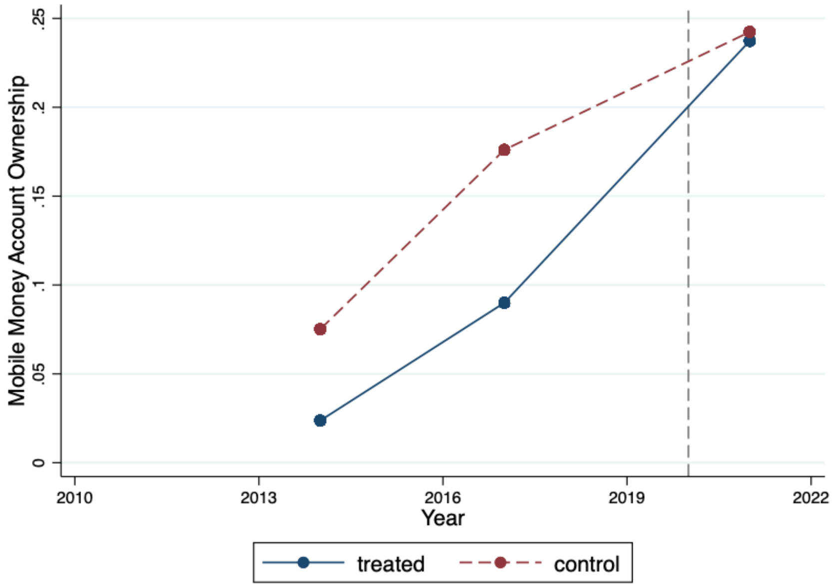
To estimate a causal effect, I need to assume that without COVID-19, financial adoption patterns would have developed in the same pattern in low- and high-exposure countries. Using two or three (years 2011, 2014, and 2017) pre-treatment observations for fintech adoption, Figure 4.1 and Figure 4.2 show that, prior to 2020, there are parallel trends in fintech access and the use of fintech. Looking at the raw data, Figure 4.1 shows that mobile money account ownership indeed increases more strongly in the high-exposure countries after the pandemic. Figure 4.2 shows the event study for the treatment dynamic effects on debit or credit card ownership. It shows that before the COVID-19 treatment in 2020, high pandemic affectedness has no significantly positive effects on debit or credit card ownership, but after the treatment year 2020, the treatment effect is significantly positive. Given the data limitation, I am unable to provide multiple-period pre-trends for all fintech adoption variables, but the figures show that the parallel trend assumption is satisfied for the variables I have the complete pre-treatment data.

I analyse this difference-in-differences systematically using the regression

$$FintechAdoption_{ct} = \beta_0 + \beta_1 HighExpousre_c * After_t + \alpha_c + Year_t + X'_{ct}\theta + \epsilon_{ct} \quad (4.4)$$

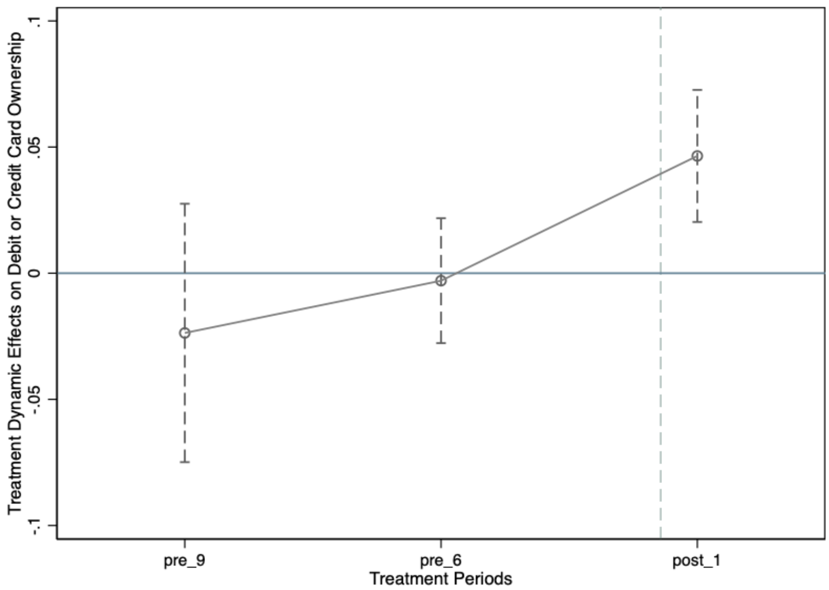
where $FintechAdoption_{ct}$ is the financial technology adoption level for country c in year t, i.e., the access to financial technology and the use of such technologies. Here X_{ct} is a set of time-variant country characteristics, including GDP per capita, population age structure, internet infrastructure, and governance capacity. Country fixed effects (α_c) and year fixed effects ($Year_t$) capture state- and year-specific factors affecting financial technology adoption. $HighExpousre_c$ is an indicator variable equal to 1 when country c has exposure intensity above the sample average level, equal to 0 otherwise. $After_t$ is an

Figure 4.1: Raw Change in Mobile Money Account Ownership for High versus Low COVID-Affectedness Countries



Notes: This figure shows a simple average level of mobile money account ownership for highly pandemic affected countries (whose exposure intensity is higher than 0.406) and lower pandemic affected countries (whose exposure intensity is below 0.406) in 2014, 2017, and 2021. (There is no such data in 2011.)

Figure 4.2: Event Study for Dynamic Effects on Debit or Credit Card Ownership



Notes: This figure displays coefficients and 95% confidence intervals from regressions of debit or credit card ownership on leads and lags of the interaction of the dummy variable for time with high pandemic affectedness. The year 2017 is taken as the reference period. The dashed vertical line indicates the treatment year: 2020.

indicator variable equal to 1 when the year is after 2020 (the year when COVID-19 started to spread over the world[3]), equal to 0 when the year is before 2020. Their interaction β_1 is my main variable of interest, capturing the effect of high-pandemic-affectedness treatment.

4.4 Combination of IV and DiD Approaches

As I mentioned before, the pandemic exposure intensity captures the impacts of COVID-19 on both public health and government policy responses. Therefore, there may be some measurement errors for the actual COVID-19 affectedness in different countries. The measurement errors could bias the difference-in-differences estimates obtained by the specification (4.4) in the last subsection. To deal with this concern, I combine the IV approach and the DiD approach. Specifically, I instrument the intensity of exposure to COVID-19 with the number of airports and the time of the first confirmed COVID case in a country (as shown in the first stage equation (4.2) in section 4.2). Then I use the predicted exposure intensity in the following second-stage specification:

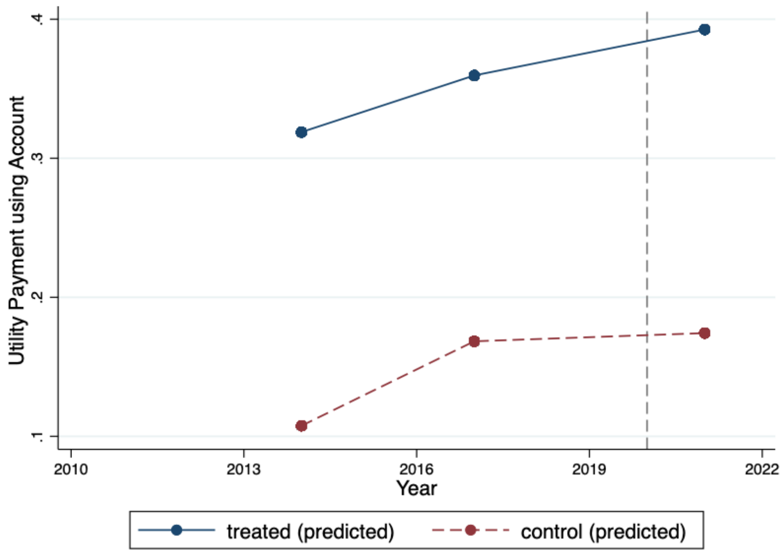
$$FintechAdoption_{ct} = \beta_0 + \beta_1 High\widehat{Expousre}_c * After_t + \alpha_c + Year_t + X'_{ct}\theta + \epsilon_{ct} \quad (4.5)$$

This model is equivalent to the DiD specification (4.4) shown in the last subsection, but it uses the predicted exposure intensity, rather than the direct exposure intensity measurement. The coefficient of interest, β_1, now accounts for possible measurement errors with the help of the two instruments.

Similar to Figures 4.1 and 4.2, Figures 4.3 and 4.4 show the pre-treatment trends in fintech access and daily use, but the high-pandemic-affectedness treatment is based on the first-stage prediction. Figure 4.3 shows that there is indeed a similar evolving pattern in utility payment using accounts before COVID-19. The event study for the treatment dynamic effects on debit or credit card ownership in Figure 4.4 indicates the treatment effects of high pandemic affectedness are not significantly different from zero before the treatment. Figures 4.3 and 4.4 confirm that the parallel trend assumption required by the IV-DiD approach is satisfied.

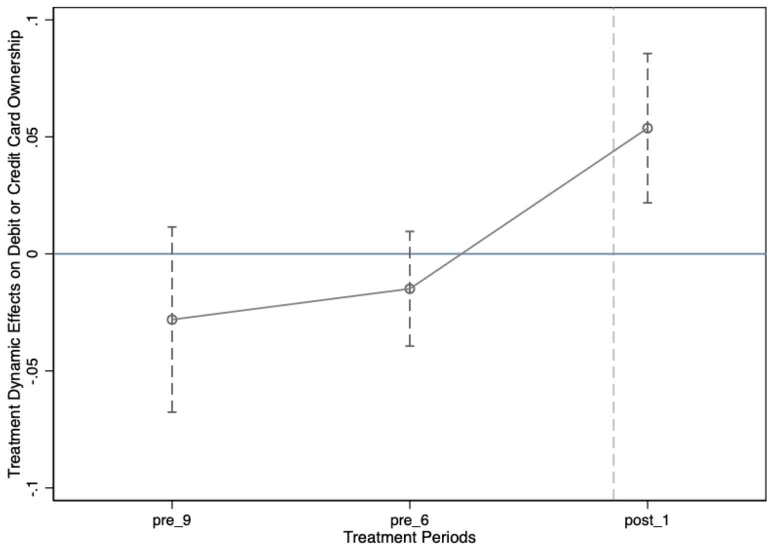
[3]Although COVID-19 began to appear in December 2019, for most countries, 2020 is when the pandemic spread in their countries.

Figure 4.3: Raw Change in Utility Payment using Account for High (predicted) versus Low (predicted) COVID-affected Countries



Notes: This figure shows a simple average level in utility payment using an account for highly pandemic affected countries (whose predicted exposure intensity is higher than 0.373) and lower pandemic affected countries (whose predicted exposure intensity is below 0.373) in 2014, 2017, and 2021. I use the predicted exposure intensity obtained from the first-stage estimation rather than the actual exposure intensity. (There is no such data in 2011.)

Figure 4.4: Events Study for Dynamic Effects on Debit or Credit Card Ownership (Predicted Treatment)



Notes: This figure displays coefficients and 95% confidence intervals from regressions of debit or credit card ownership on leads and lags of the interaction of the dummy variable for time with high pandemic affectedness. The pandemic affectedness is obtained from the first-stage estimation using two instruments. The year 2017 is taken as the reference period. The dashed vertical line indicates the treatment year: 2020.

5 Main Results

This section reports my main results on the effects of pandemic exposure intensity on financial technology adoption: access to financial technologies and the daily use of financial technologies.

5.1 Results for Simple OLS

As a starting point, Table 5.1 reports the results of impacts on fintech access using the OLS specification, and Table 5.2 reports the OLS results of impacts on fintech use. In the first column of Table 5.1, it shows one unit of increase in exposure intensity would cause a statistically significant and positive effect (around 10%) on financial account ownership, while for debit and credit card ownership (column 2), there is a much smaller but still positive effect (4.4%). Interestingly, for the mobile money account ownership, there is a negative but not significant effect of exposure intensity (-1.5%). Moreover, the number of observations (country) changes from 118 to 58 because the use of mobile money services is mainly concentrated in developing economies, especially in the Sub-Saharan Africa region. For these three outcome variables, the results show that the fintech access level in the last survey (baseline level in year 2017) has negative effects on changes in fintech access, and it fits the situation that there is less space for further improvement in access to financial technologies for countries that already have a high level of fintech access. Combining these three variables, I find a positive impact on the first two main indicators, despite a negative effect on mobile money account ownership (likely due to endogenous concerns). The simple OLS regression may not fully reflect the true impact, but it still provides a preliminary reference for the positive effects of COVID-19 exposure intensity on financial technology access.

Table 5.1: OLS Results for Effect of Pandemic Exposure Intensity on Fintech Access

	(1) Change in Account Ownership	(2) Change in Debit and Credit Card Ownership	(3) Change in Mobile Money Account Ownership
Exposure Intensity	0.100**	0.044	-0.015
	(0.045)	(0.043)	(0.107)
GDP per Capita	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Population Age Structure	0.002	0.004***	0.003
	(0.001)	(0.001)	(0.005)
Internet Access	0.000	0.001**	0.000
	(0.000)	(0.000)	(0.001)
Governance Capacity	-0.005	-0.013	-0.006
	(0.016)	(0.015)	(0.035)
Fintech Access in Last Survey	-0.107**	-0.115**	-0.067
	(0.049)	(0.050)	(0.117)
Constant	0.022	-0.136***	0.017
	(0.038)	(0.034)	(0.105)
N	118	118	58

Notes: This table shows OLS regression of changes in financial technology access with pandemic exposure intensity and a series of country characteristics. Column (1) presents results for change in adults' account ownership, and column (2) shows results for change in debit and credit card ownership. Column (3) reports results for change in mobile money account ownership. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 5.2 shows similar positive effects on the various daily use of financial technologies, except for using the mobile money service and change in digital payment online because they show negative effects of exposure intensity. The negative impact might be caused by the estimation bias. Compared with the effects on fintech access, the effects on fintech use are relatively smaller in magnitude and the effects of exposure intensity are all below 10%. Specifically, for change in debit and credit card use, one unit increase in exposure intensity would generate a 7.3 percent rise in individuals' usage of such financial cards. There would be around a 5 percent increase in daily digital payments induced by one-unit higher pandemic exposure intensity. The impact on change in utility payment using an account is larger (near 0.10) and statistically significant.

Table 5.2: OLS Results for Effect of Pandemic Exposure Intensity on Fintech Use

	(1) Change in Debit and Credit Card Use	(2) Mobile Money Use	(3) Change in Digital Payment	(4) Change in Phone or Internet Bill	(5) Digital Payment in Store	(6) Change in Digital Payment Online	(7) Digital Merchant Payment	(8) Change in Utility Payment using Account
Exposure Intensity	0.073	-0.116	0.050	0.033	0.051	-0.022	0.053	0.095**
	(0.045)	(0.121)	(0.051)	(0.064)	(0.132)	(0.120)	(0.133)	(0.045)
GDP per Capita	-0.000*	0.000	-0.000	-0.000*	0.000***	-0.000**	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population Age Structure	0.004**	-0.011**	0.004**	0.003	0.015***	0.004	0.015***	0.005***
	(0.002)	(0.005)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.001)
Internet Access	0.000	-0.000	-0.000	0.001	0.000	0.003	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Governance Capacity	0.004	0.007	-0.004	0.014	0.025	0.031	0.031	0.007
	(0.016)	(0.037)	(0.018)	(0.023)	(0.042)	(0.032)	(0.042)	(0.016)
Fintech Use in Last Survey	-0.013		-0.090*	-0.090		0.382*		-0.190***
	(0.049)		(0.052)	(0.076)		(0.186)		(0.054)
Constant	-0.110***	0.460***	0.027	-0.004	-0.231***	-0.197	-0.224**	-0.062*
	(0.041)	(0.083)	(0.041)	(0.050)	(0.087)	(0.169)	(0.088)	(0.035)
N	101	44	118	118	90	32	90	118

Notes: This table shows OLS regression of changes in the daily use of financial technologies with pandemic exposure intensity, a series of country characteristics, and the fintech use level in the last survey (2017). *** significant at 1%; ** significant at 5%; * significant at 10%.

5.2 Results for the IV Approach

Table 5.3 and Table 5.4 report the estimation results for the effects of exposure intensity on fintech access and fintech use respectively, using the IV approach. Compared with the estimates from OLS, it is clear that the estimates obtained by the IV approach are much larger in magnitude. For three variables on fintech access, the impacts on both changes in account ownership and debit and credit card ownership have nearly doubled (from 0.100 to 0.186 and from 0.044 to 0.108, respectively). The effect of pandemic exposure intensity on mobile money account ownership is totally different from the OLS estimation result, and the coefficient becomes positive and significantly larger. The same situation happens to the impacts on the use of fintech. All the coefficients on financial card use and various digital payments have also at least doubled, and the negative effects of exposure intensity from the OLS estimation turn positive. Therefore, the simple OLS causes the coefficient to be downward biased and underestimates the effects of exposure intensity on fintech access and the use of financial technologies. I could consider that pandemic exposure intensity has economically larger effects on fintech adoption.

Although the coefficients are not statistically significant at the 95% or even 90% confidence levels, the p-values of the interested coefficients (on $ExposureIntensity$) are almost between 10% and 30%. For the statistical insignificance, I consider the main reason to be the problem of weak instrument variables. In this thesis, I use the number of airports and the time of the first confirmed COVID case in a country to instrument the intensity of exposure to the pandemic. Although these two variables have statistically significant impacts on exposure intensity (as shown in the first stage), the Cragg-Donald Wald F statistic in the weak IV testing is 7.11, which is slightly smaller than 10 (the generally accepted threshold for weak instrumental variables), so I cannot reject the hypothesis that the instrument variables are weak. I have to admit that it is difficult to find an ideal IV to perfectly instrument the pandemic exposure intensity at a global level given the strong heterogeneity among countries. Although this thesis does not provide an ideal IV, it still provides a meaningful attempt to isolate the exogenous part from the endogenous exposure intensity and identify the causal relationship between pandemic exposure and financial technology adoption.

Table 5.3: IV Results for Effect of Pandemic Exposure Intensity on Fintech Access

	(1) Change in Account Ownership	(2) Change in Debit and Credit Card Ownership	(3) Mobile Money Account Ownership
Exposure Intensity	0.186	0.108	0.252
	(0.210)	(0.201)	(0.306)
GDP per Capita	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Population Age Structure	0.001	0.003	-0.002
	(0.003)	(0.003)	(0.006)
Internet Access	0.000	0.001**	0.000
	(0.001)	(0.001)	(0.001)
Governance Capacity	0.000	-0.006	-0.002
	(0.017)	(0.016)	(0.037)
Fintech Access in Last Survey	-0.092*	-0.101**	0.948***
	(0.051)	(0.048)	(0.116)
Constant	0.030	-0.123***	0.049
	(0.040)	(0.038)	(0.105)
N	117	117	57

Notes: This table shows the second stage regression results of changes in the financial technology access with pandemic exposure intensity, a series of country characteristics, and the fintech access level in the last survey (2017). *** significant at 1%; ** significant at 5%; * significant at 10%.

5.3 Results for the DiD Approach

Table 5.5 and Table 5.6 report the estimation results for the effects of exposure intensity on fintech access and the use of fintech respectively, using the DiD approach. The interested coefficients are for the interaction term $HighExpousre_c * After_t$. In contrast to the estimation results given by the IV approach, most of the interested coefficients are statistically significant and positive. The results show that treated countries with high COVID-19 affectedness experience more financial technology adoption (around 5% on average), both in the access to financial technologies and in the daily use of fintech. As demonstrated in column 2 and column 3 of Table 5.5, countries highly affected by the COVID-19 pandemic experience approximately 6 percent higher ownership of debit and credit cards and mobile money accounts. The treatment impact on account ownership is relatively smaller in magnitude (0.017). The treatment effects of high pandemic affectedness on fintech usage are significantly larger than on fintech access. Column 1 and column 3 of Table 5.6 indicate that the high COVID-19 affectedness treatment could generate an over 6 percent jump in using bank cards and using accounts to pay utility bills. Therefore, it appears that the positive impacts of exposure intensity obtained by

Table 5.4: IV Results for Effect of Pandemic Exposure Intensity on Fintech Use

	(1) Change in Debit and Credit Card Use	(2) Mobile Money Use	(3) Change in Digital Payment	(4) Change in Phone or Internet Bill	(5) Digital Payment in Store	(6) Change in Digital Payment Online	(7) Digital Merchant Payment	(8) Change in Utility Payment using Account
Exposure Intensity	0.154	0.101	0.186	0.292	0.697	0.592	0.682	0.171
	(0.120)	(0.326)	(0.241)	(0.185)	(0.512)	(0.550)	(0.514)	(0.123)
GDP per Capita	-0.000	0.000	-0.000	-0.000	0.000***	-0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population Age Structure	0.003	-0.011*	0.001	-0.001	0.006	-0.005	0.006	0.005**
	(0.002)	(0.006)	(0.004)	(0.003)	(0.009)	(0.009)	(0.009)	(0.002)
Internet Access	0.000	-0.000	-0.000	0.000	-0.001	0.002	-0.000	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Governance Capacity	0.006	0.018	0.005	0.024	0.006	0.015	0.014	0.007
	(0.016)	(0.037)	(0.019)	(0.024)	(0.048)	(0.042)	(0.048)	(0.016)
Fintech Use in Last Survey	-0.010		-0.066	-0.093		0.477*		-0.195***
	(0.048)		(0.052)	(0.079)		(0.249)		(0.053)
Constant	-0.106***	0.438***	0.043	0.023	-0.190*	-0.167	-0.182*	-0.057
	(0.041)	(0.078)	(0.046)	(0.055)	(0.102)	(0.216)	(0.103)	(0.037)
N	101	45	117	117	89	32	89	117

Notes: This table shows the second stage regression results of changes in the daily use of financial technologies with pandemic exposure intensity, a series of country characteristics, and the fintech use level in the last survey (2017). *** significant at 1%; ** significant at 5%; * significant at 10%.

the IV approach indeed exist, and the insignificance of IV results may be caused by the weak IV problem.

Table 5.5: DiD Results for Effect of Pandemic Exposure Intensity on Fintech Access

	(1) Account Ownership	(2) Debit and Credit Card Ownership	(3) Mobile Money Account Ownership
HighExpousre∗After	0.017	0.056***	0.060*
	(0.018)	(0.016)	(0.032)
GDP per Capita	-0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)
Population Age Structure	-0.012	0.030***	-0.053***
	(0.007)	(0.007)	(0.017)
Internet Access	0.003***	0.002***	0.002**
	(0.001)	(0.001)	(0.001)
Governance Capacity	0.075**	0.001	-0.039
	(0.037)	(0.034)	(0.072)
Constant	1.450***	-0.660**	1.627**
	(0.325)	(0.299)	(0.714)
Country FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
N	465	465	189

Notes: This table shows the DiD regression of the financial technology access with the interaction of high pandemic exposure intensity with the time indicator and a series of country characteristics. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 5.6: DiD Results for Effect of Pandemic Exposure Intensity on Fintech Use

	(1) Debit and Credit Card Use	(2) Phone or Internet Bill	(3) Utility Payment using Account
HighExpousre∗After	0.063***	0.048**	0.065***
	(0.015)	(0.020)	(0.015)
GDP per Capita	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Population Age Structure	0.025***	0.015	0.018**
	(0.009)	(0.017)	(0.008)
Internet Access	0.001	0.002*	0.001
	(0.001)	(0.001)	(0.001)
Governance Capacity	0.052	0.062	0.024
	(0.039)	(0.065)	(0.038)
Constant	-0.369**	-0.034	-0.102
	(0.151)	(0.274)	(0.369)
Country FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
N	311	241	351

Notes: This table shows the DiD regression of the financial technology daily use with the interaction of high pandemic exposure intensity with the time indicator and a series of country characteristics. *** significant at 1%; ** significant at 5%; * significant at 10%.

5.4 Results for the Combination of IV and DiD

Table 5.7 and Table 5.8 report the estimation results for the effects of exposure intensity on fintech access and the use of fintech respectively, using the IV-DiD approach. The interested coefficients are for the interaction term $High\widehat{Expousre}_c * After_t$. Comparing Table 5.5 and Table 5.7, although coefficients for debit and credit card ownership are quite similar (0.056 versus 0.054), there are some deviations in the coefficients for account ownership and mobile money account ownership. Specifically, the classical DiD shows that the high-pandemic-affectedness treatment has positive impacts on account ownership and mobile money account ownership (0.017 and 0.060, respectively). However, the IV-DiD indicates that the treatment effect on account ownership is insignificantly negative (-0.020), and the effect on mobile money account ownership becomes smaller in magnitude (0.034). Comparing Table 5.6 and Table 5.8, it also shows the treatment effect on utility payment using account is halved (from 0.065 to 0.031), but there are no major changes in treatment effects on debit and credit card use and paying bills with phone or Internet. From the comparison between classical DiD and IV-DiD, it appears that although there are some deviations in treatment effects with two different specifications, the treatment effects on fintech adoption are generally similar. Therefore, it confirms again that pandemic exposure intensity has significantly positive impacts on financial technology adoption.

Table 5.7: IV-DiD Results for Effect of Pandemic Exposure Intensity on Fintech Access

	(1) Account Ownership	(2) Debit and Credit Card Ownership	(3) Mobile Money Account Ownership
$\widehat{HighExpousre}$∗After	-0.020	0.054***	0.034
	(0.017)	(0.014)	(0.030)
GDP per Capita	-0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)
Population Age Structure	-0.011	0.026***	-0.051***
	(0.007)	(0.006)	(0.018)
Internet Access	0.003***	0.002***	0.002**
	(0.001)	(0.000)	(0.001)
Governance Capacity	0.070**	0.003	-0.028
	(0.033)	(0.028)	(0.074)
Constant	1.494***	-0.505**	1.576**
	(0.286)	(0.244)	(0.728)
Country FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
N	465	465	189

Notes: This table shows the DiD regression of the financial technology access with the interaction of predicted high pandemic exposure intensity (from the first-stage estimation using two instruments) with the time indicator and a series of country characteristics. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 5.8: IV-DiD Results for Effect of Pandemic Exposure Intensity on Fintech Use

	(1) Debit and Credit Card Use	(2) Phone or Internet Bill	(3) Utility Payment using Account
$\widehat{HighExpousre}$∗After	0.072***	0.046**	0.031*
	(0.018)	(0.021)	(0.016)
GDP per Capita	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Population Age Structure	0.022**	0.010	0.019**
	(0.009)	(0.017)	(0.009)
Internet Access	0.001	0.002	0.001
	(0.001)	(0.001)	(0.001)
Governance Capacity	0.051	0.060	0.018
	(0.039)	(0.065)	(0.039)
Constant	-0.318**	0.039	-0.186
	(0.152)	(0.281)	(0.382)
Country FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
N	311	241	351

Notes: This table shows the DiD regression of the financial technology daily use with the interaction of predicted high pandemic exposure intensity (from the first-stage estimation using two instruments) with the time indicator and a series of country characteristics. *** significant at 1%; ** significant at 5%; * significant at 10%.

6 Robustness Checks

In this section, I check the robustness of the main results by using alternative outcome variables and changing the sample size.

6.1 Alternative Dependent Variables

Firstly, the dependent variable in this paper, fintech adoption, is measured with the changes in individuals' access and daily use of financial cards, mobile money and digital payment in the previous analysis. In the Global Findex Database 2021, given the situation that almost all countries have experienced the COVID-19 pandemic, there are some specific questions in the survey investigating fintech adoption directly linked to the pandemic. As shown below, these questions investigate people's initial adoption of digital payment in their daily life directly related to the pandemic, including merchant purchasing and utility fee payment. Therefore, in the first robustness check, I use the following alternative measurements for fintech adoption to check whether the positive effects of the pandemic exposure intensity on fintech adoption still exist:

- The percentage of respondents who report making a digital in-store merchant payment for the first time after COVID-19 started.
- The percentage of respondents who report making a digital merchant payment for the first time after COVID-19 started.
- The percentage of respondents who report making a utility payment using an account for the first time after COVID-19 started.

According to the report from the World Bank (Demirgüç-Kunt et al., 2022), the COVID-19 pandemic expedited an increase in the proportion of individuals who use accounts to pay utility bills and people who make digital merchant payments in developing economies. In the report, researchers show that over thirty percent of adults from less-developed countries paid their daily utility bills using an account for the first time in 2021 when the pandemic was spreading vigorously over their countries. Moreover, this trend was particularly strong in some Latin American countries. In Peru, for example, nearly one-fifth of adults started their first utility fee payments using an account during the COVID-19 time, accounting for more than sixty percent of people who took such payment method. There was also around one-fifth of adults who made such payments using an account for the first time in Brazil, nearly doubling the original ratio. In fact, these two countries are also nations with higher pandemic exposure intensity in my sample, as shown in Table 3.1. At the same time, developing countries also experience a large increase in the proportion of individuals making digital merchant payments. Still in Brazil, around one-fifth of adults made their first digital merchant payment after the widespread transmission of COVID-19. Some scholars speculate that social distancing and contamination concerns during the pandemic may have played an important role in this process, and these conjectures will be confirmed in subsequent sections.

Table 6.1 reports the estimation results using these different measurements for the dependent variable. OLS results in columns 1, 3 and 5 show relatively small and even negative effects on daily digital payment activities. The results obtained using the IV approach in columns 2, 4 and 6 indicate that the exposure intensity has an economically significant and much more positive impact on daily digital payment, using the alternative financial technology adoption measurements. Specifically, for making digital merchant payments in stores, the OLS estimation result indicates a negative impact of the pandemic exposure intensity (one unit increase in exposure intensity would induce around a 6.6 percent decrease in such digital in-store merchant payment share). For a more general digital merchant payment (in-store, online, or other forms), this negative effect still appears. While for paying utility bills using an account for the first time, the impact of exposure intensity becomes positive (one unit increase in exposure intensity would cause about a 6.7 percent increase in such share). However, the estimation results obtained by the IV approach are quite different. The estimates all become positive in the direction, and larger in magnitude. One unit increase in pandemic exposure intensity could generate around a 26 percent jump in both digital in-store merchant payment and more general digital merchant payment, and this effect is even over 30 percent for utility payments using an account for the first time after COVID-19. It is clear that the IV second-stage estimation results are similar to those in the main analysis and therefore I claim that the results are robust to the alternative outcome variables.

Table 6.1: OLS and IV Results for Effect of Pandemic Exposure Intensity on Alternative Fintech Adoption

	(1) Digital Payment in Store after COVID (OLS)	(2) Digital Payment in Store after COVID (IV)	(3) Digital Merchant Payment after COVID (OLS)	(4) Digital Merchant Payment after COVID (IV)	(5) Utility Payment Using Account after COVID (OLS)	(6) Utility Payment Using Account after COVID (IV)
Exposure Intensity	-0.066	0.256	-0.059	0.268	0.067	0.335
	(0.042)	(0.274)	(0.047)	(0.290)	(0.040)	(0.228)
GDP per Capita	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population Age Structure	0.000	-0.004	0.000	-0.005	-0.001	-0.005
	(0.001)	(0.004)	(0.001)	(0.005)	(0.001)	(0.004)
Internet Access	0.001	0.000	0.001*	0.001	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Governance Capacity	0.002	-0.009	0.002	-0.006	-0.029**	-0.039**
	(0.013)	(0.021)	(0.015)	(0.022)	(0.014)	(0.020)
Constant	0.071**	0.062	0.065*	0.052	0.053*	0.067*
	(0.034)	(0.049)	(0.035)	(0.047)	(0.029)	(0.040)
N	57	56	59	58	59	59

Notes: This table shows the OLS and IV's second stage regression results of alternative daily use of financial technologies specifically related to COVID-19 with pandemic exposure intensity and a series of country characteristics. *** significant at 1%; ** significant at 5%; * significant at 10%.

6.2 Sensitivity to Developing Countries Subsample

The main analysis includes both developed countries and developing countries. Since developed countries have higher economic development levels, better internet infrastructure, and better regulated financial industries, they had very high fintech adoption levels before the outbreak of COVID-19. Developed countries have limited space for further improvement given their high base of fintech adoption levels. At the same time, this paper uses the differences in fintech access and daily use between 2021 and 2017, which causes the COVID-19 pandemic shock to have a smaller effect on fintech adoption among developed countries. It is a different story in developing countries; the intensity of exposure to COVID-19 would have relatively larger positive effects for developing countries. Therefore, I use the developing-countries subsample to re-estimate the effect of the intensity of exposure to COVID-19 on changes in fintech adoption among this subsample. If the effects of COVID-19 exposure intensity on fintech adoption among all economies are positive, we would expect that the positive effects of exposure intensity are larger for the developing countries subsample.

Table 6.2 and Table 6.3 separately report the IV second-stage estimation results for fintech access and the use of fintech among developing countries. Compared with Table 5.3 in the main analysis, the effects on fintech access among developing countries in Table 6.2 are much larger in magnitude. Specifically, the impacts of pandemic exposure intensity on change in account ownership and change in debit and credit card ownership have more than doubled, from 0.186 to 0.446 and from 0.108 to 0.266, respectively. For mobile money account ownership, there is a smaller jump in the impact (from 0.252 to 0.348), but it is the situation that mobile money service mainly is provided among developing countries. The similar pattern also occurs in the comparison between Table 5.4 and Table 6.3. Although there are slight declines in effects on some fintech use variables (mobile money and digital payment), the remaining variables also witness a jump in impacts, even the impact of exposure intensity on change in utility payment using account has tripled. The results confirm that the intensity of exposure to COVID-19 has a positive effect on fintech access and the use of financial technologies, and the effects are heterogeneous among different development stages. For developing countries with a lower baseline level of financial technology adoption, the pandemic shock generates more significant impacts on the adoption process.

Table 6.2: IV Results for Effect of Pandemic Exposure Intensity on Fintech Access among Developing Countries

	(1) Change in Account Ownership	(2) Change in Debit and Credit Card Ownership	(3) Mobile Money Account Ownership
Exposure Intensity	0.446	0.266	0.348
	(0.313)	(0.270)	(0.412)
GDP per Capita	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Population Age Structure	-0.003	-0.000	-0.004
	(0.005)	(0.004)	(0.007)
Internet Access	-0.000	0.001*	0.001
	(0.001)	(0.001)	(0.001)
Governance Capacity	0.006	-0.007	-0.003
	(0.026)	(0.021)	(0.038)
Fintech Access in Last Survey	-0.036	-0.034	0.974***
	(0.073)	(0.067)	(0.123)
Constant	0.018	-0.112**	0.041
	(0.054)	(0.045)	(0.114)
N	80	80	55

Notes: This table shows the IV's second stage regression results of financial technology access with pandemic exposure intensity on a series of country characteristics, and fintech access level in the last survey (2017) in developing countries. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 6.3: IV Results for Effect of Pandemic Exposure Intensity on Fintech Use among Developing Countries

	(1) Change in Debit and Credit Card Use	(2) Mobile Money Use	(3) Change in Digital Payment	(4) Change in Phone or Internet Bill	(5) Digital Payment in Store	(6) Change in Digital Payment Online	(7) Digital Merchant Payment	(8) Change in Utility Payment using Account
Exposure Intensity	0.413	0.039	0.522	0.820	0.541	0.492	0.530	0.608*
	(0.284)	(0.376)	(0.380)	(0.503)	(0.562)	(0.465)	(0.566)	(0.349)
GDP per Capita	-0.000	0.000	-0.000	0.000	0.000**	-0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population Age Structure	-0.003	-0.014**	-0.004	-0.012	0.006	-0.005	0.006	-0.004
	(0.005)	(0.006)	(0.006)	(0.008)	(0.008)	(0.007)	(0.008)	(0.006)
Internet Access	0.000	0.000	-0.000	-0.000	-0.001	0.003	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Governance Capacity	0.013	0.014	0.013	0.018	-0.034	0.036	-0.027	-0.005
	(0.025)	(0.036)	(0.029)	(0.038)	(0.048)	(0.048)	(0.049)	(0.027)
Fintech Use in Last Survey	0.162*		0.023	0.336		0.808**		-0.113
	(0.089)		(0.081)	(0.216)		(0.335)		(0.118)
Constant	-0.065	0.476***	0.043	0.096	-0.183*	-0.171	-0.172*	-0.007
	(0.053)	(0.084)	(0.062)	(0.081)	(0.098)	(0.215)	(0.099)	(0.056)
N	64	43	80	80	79	22	79	80

Notes: This table shows the IV's second stage regression results of financial technology daily use with pandemic exposure intensity on a series of country characteristics, and fintech use level in the last survey (2017) in developing countries. *** significant at 1%; ** significant at 5%; * significant at 10%.

6.3 Different Measurements of Dependent Variables

In the main analysis, I use the difference between 2021 and 2017 in fintech adoption in each country. There are four rounds of Global Findex surveys in 2011, 2014, 2017, and 2021. Therefore, instead of just using the difference between 2021 and 2017, I can also use the difference between 2021 and 2014 or between 2021 and 2011. Considering the limited data quality and integrity, namely, there are many missing data for some variables and the unsurveyed questions, in the first round of surveys in 2011, I use the difference between 2021 and 2014 for fintech access and daily use as the alternative dependent variables. If the effects of COVID-19 exposure intensity on fintech adoption between 2021 and 2017 are significant, I expect that similar positive effects also exist on fintech adoption between 2021 and 2014.

Table 6.4 and Table 6.5 separately report the estimation results for the new differences between 2021 and 2014 in fintech access and fintech daily use with the IV approach. Comparing Table 5.3 with Table 6.4, although there are some deviations in the estimated results, the coefficients are quite similar in magnitude and direction. Specifically, there is a slight increase in the impact of pandemic exposure intensity on change in account ownership for the difference between 2021 and 2014 (from 0.186 to 0.244), while a modest decrease happens in the impact on change in debit and credit card ownership (from 0.108 to 0.063). For the effects of exposure intensity on mobile money account ownership, they are quite similar for two different time ranges (0.252 and 0.272). Therefore, the positive effects of exposure intensity on fintech access appear to be robust to the alternative differences between 2021 and 2014. I find a similar situation when comparing Table 5.4 and Table 6.5 and thus the positive impacts on the use of fintech also appear to be robust.

Table 6.4: IV Results for Effect of Pandemic Exposure Intensity on Alternative Fintech Access

	(1) Change in Account Ownership	(2) Change in Debit and Credit Card Ownership	(3) Mobile Money Account Ownership
Exposure Intensity	0.244	0.063	0.272
	(0.168)	(0.261)	(0.392)
GDP per Capita	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Population Age Structure	-0.000	0.006	-0.011
	(0.003)	(0.004)	(0.007)
Internet Access	-0.001	0.002**	0.001
	(0.001)	(0.001)	(0.002)
Governance Capacity	0.035	-0.004	0.021
	(0.022)	(0.021)	(0.050)
Fintech Access in Last Survey	-0.291***	-0.202***	0.941***
	(0.063)	(0.066)	(0.219)
Constant	0.263***	-0.146***	0.305**
	(0.050)	(0.048)	(0.124)
N	113	113	53

Notes: This table shows the IV's second stage regression results of change in financial technology access (between 2021 and 2014) with pandemic exposure intensity on a series of country characteristics, and fintech access level in the last survey (2014). *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 6.5: IV Results for Effect of Pandemic Exposure Intensity on Alternative Fintech Use

	(1) Change in Debit and Credit Card Use	(2) Change in Digital Payment	(3) Change in Utility Payment using Account
Exposure Intensity	0.133	0.175	0.241
	(0.171)	(0.194)	(0.164)
GDP per Capita	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Population Age Structure	0.008***	0.003	0.005*
	(0.003)	(0.003)	(0.003)
Internet Access	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Governance Capacity	-0.010	0.023	0.004
	(0.025)	(0.025)	(0.021)
Fintech Use in Last Survey	-0.160**	-0.268***	-0.331***
	(0.078)	(0.072)	(0.071)
Constant	-0.232***	0.198***	-0.031
	(0.068)	(0.058)	(0.052)
N	93	113	109

Notes: This table shows the IV's second stage regression results of change in financial technology daily use (between 2021 and 2014) with pandemic exposure intensity on a series of country characteristics, and fintech use level in the last survey (2014). *** significant at 1%; ** significant at 5%; * significant at 10%.

7 Mechanism Exploration

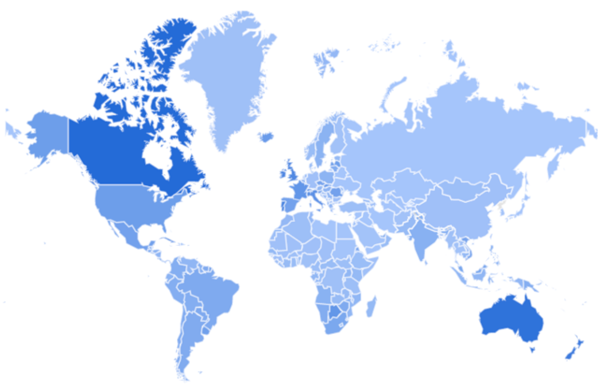
The estimation results above show that a higher intensity of exposure to COVID-19 induces countries to experience higher fintech adoption. I consider one possible mechanism behind this finding to be that a higher intensity of exposure to COVID-19 (that is, higher infection and death rates, and stricter government policy responses) causes people to be more concerned about the COVID-19 situation in their countries. Individuals then choose to adopt financial technologies instead of visiting brick-and-mortar branches and relying on conventional approaches to mitigate infection risks and avoid various policy restrictions, such as lockdowns or workplace closures.

According to the World Health Organization (WHO, 2022), during the initial year of the COVID-19 pandemic, factors including social distancing, constraints on people's daily activities, apprehension of infection, and other concerns triggered a 25% upsurge in the occurrence of anxiety and depression across the world. Breslau et al. (2021) employ longitudinal data from the Rand American Life Panel to assess the impact of the COVID-19 pandemic on psychological distress levels among Americans. They find that the disruption in regular life order and daily routines caused by COVID-19 increases psychological distress among 12.8% of the sample relative to the highest distress level before COVID-19. Moreover, the increase in distress was more common among women, younger people, and lower-income populations.

To check whether this proposed mechanism is justifiable, I use the Google search trend to track the public's stress and concerns about the COVID-19 situation. Ripberger (2011) discusses in detail the feasibility and validity of using internet search trends to measure public attention. Indeed, using Google search trends as an indicator of public attentiveness is a plausible method to measure people's perceptions, based on two situations. One is the dominance of Google in the search engine market. Although there are slight fluctuations in the market shares of search engines worldwide from 2015 to 2023, Google has been consistently holding more than 84% of the global search engines market, while the shares of all other search tool engines (such as Yahoo, Bing, and Yandex) have been rather lopsided (https://www.statista.com/). The other is the proper measurement of Google search because the search data collected by Google Trends allows us to track how often a particular term is invoked as compared with the total number of searches done on Google across specific countries, categories, and time frames. Therefore, popularity and flexible data collection make Google search trends an apt measure of people's perceptions during the COVID-19 pandemic.

I use the Google search trend for the term 'COVID' in different countries during the year 2021 to measure people's stress and concerns related to the COVID-19 pandemic. When the pandemic is spreading over the country, people are eager to learn more information about the pandemic, such as suspected symptoms of COVID-19 infection, effective prevention measures, and up-to-date local transmission status. When people are more concerned about the current pandemic situation and the impact of the epidemic on themselves, they may resort to commonly used search engines and search for more information about the pandemic on the Internet. During their information search process, any search related to the COVID-19 pandemic would inevitably involve the key term 'COVID'. Therefore, the term 'COVID' can broadly capture people's distress level with regard to the pandemic. The figure below shows the Google search trend for the term 'COVID' across countries, with the darker countries having higher search levels than lighter countries.

Figure 7.1: Google Search Trend for Term 'COVID' across Countries in 2021



Notes: Google search volume across countries spanning from 01/01/2021 to 31/12/2021. *Source:* https://trends.google.com/

I use the same specification (equation (4.1)) as in the previous part to investigate whether higher intensity of exposure to the pandemic would induce people's higher stress levels related to COVID-19.

$$GoogleSearch_c = \beta_0 + \beta_1 ExposureIntensity_c + X_c^{'}\gamma + \varepsilon_c \tag{7.1}$$

where $GoogleSearch_c$ is the search volume for the term 'COVID' in country c.

Similarly, I also use two instrumental variables, namely, the number of airports and the time of the first confirmed COVID case, to identify the causal effect of the pandemic shock on COVID-related stress. The first stage is:

$$ExposureIntensity_c = \theta_0 + \theta_1 Airports_c + \theta_2 FirstCase_c + X_c^{'}\vartheta + \nu_c \tag{7.2}$$

The second stage is:

$$GoogleSearch_c = \beta_0 + \beta_1 Exposu\widehat{reInt}ensity_c + X_c^{'}\gamma + \varepsilon_c \tag{7.3}$$

where $Exposu\widehat{reInt}ensity_c$ is still the predicted intensity of exposure to the pandemic obtained from the first stage estimation.

Table 7.1 presents the findings of the estimation analysis. The first column reveals a statistically significant and positive relationship between exposure intensity and individuals' stress levels. Specifically, a one-unit increase in exposure intensity corresponds to an approximate 23-unit surge in the Google search trend index. Upon incorporating a range of country-specific factors, the estimated effects experience a modest decline while remain positive, as evidenced by columns 2 and 3. Notably, the coefficient obtained through the instrumental variable (IV) approach, as displayed in column 4, indicates a significantly larger impact of exposure intensity on online search behaviour. Consequently, these results effectively substantiate the veracity of the proposed mechanism.

Table 7.1: OLS and IV Results for Effect of Pandemic Exposure Intensity on Stress Level

	(1) COVID Search in 2021	(2) COVID Search in 2021	(3) COVID Search in 2021	(4) COVID Search in 2021
Exposure Intensity	22.838***	19.129**	20.538**	47.562*
	(7.524)	(8.970)	(8.938)	(25.246)
GDP per Capita		0.000***	0.000*	0.000**
		(0.000)	(0.000)	(0.000)
Population Age Structure		-0.132	-0.313	-0.699
		(0.266)	(0.285)	(0.453)
Internet Access		-0.008	-0.022	-0.058
		(0.095)	(0.095)	(0.101)
Governance Capacity			5.140*	5.832*
			(3.056)	(3.236)
Constant	8.611**	8.639	16.608**	19.221**
	(3.379)	(5.218)	(7.018)	(7.548)
N	120	119	119	118

Notes: This table shows OLS and IV second-stage regression of the pandemic exposure intensity with a series of country characteristics. Column (1) presents OLS results without adding any controls, and column (2) adds a country's socioeconomic factors but does not control for a country's governance capacity. Column (3) adds all the control variables, and there are no main changes in estimation results compared with columns (1) and (2). Column (4) shows IV second-stage estimation results using two instruments with adding all controls. *** significant at 1%; ** significant at 5%; * significant at 10%.

8 Conclusion

Technology transformation is essential in the development process and affects long-term economic growth. This thesis studies how an exogenous public health crisis affects the technology adoption process by investigating the impact of COVID-19 pandemic exposure intensity on the adoption of financial technologies across different countries. The estimation results obtained by multiple identification strategies reveal that a higher intensity of exposure to the pandemic leads to increased fintech adoption. This is evidenced by higher access to financial technology and more daily use of financial technology. Robustness tests with alternative outcome variables and different sample sizes further confirm the consistency of such findings. Moreover, the proposed mechanism behind these effects is validated through the analysis of Google search trends related to COVID-19, which indicate increased stress and concerns among individuals during the pandemic, subsequently driving their adoption behaviours of financial technologies.

This study contributes to the understanding of the impact of exogenous crises, such as a public health shock, on technology adoption. By focusing on fintech adoption during the COVID-19 pandemic, it sheds light on the importance of external factors and how they function on individual concerns in shaping technology adoption patterns. Furthermore, the findings of this paper provide a new perspective on understanding the impacts of COVID-19. The spread of COVID-19 around the world has caused a huge number of infections and deaths, a considerable disturbance to the international economy, and a series of negative effects on normal societal functioning. However, from historical experience, exogenous crises might also be opportunities that give rise to new favourable changes to some extent. The threats and restrictions bought about by exogenous shocks force people to adopt the latest technologies to better adapt to a crisis, rather than persistently rely on existing technologies. The crisis-induced technology adoption would unleash the potential of new technologies in promoting productivity growth and accelerating the development process. In the long run, the COVID-19 pandemic could improve the fintech adoption levels of marginalized populations and developing countries, accelerating financial inclusion on a global scale and positively impacting long-term economic development.

References

Bandiera, O. and Rasul, I. (2006). Social networks and technology adoption in northern mozambique. *The Economic Journal*, 116(514):869–902.

Breslau, J., Finucane, M. L., Locker, A. R., Baird, M. D., Roth, E. A., and Collins, R. L. (2021). A longitudinal study of psychological distress in the united states before and during the covid-19 pandemic. *Preventive Medicine*, 143:106362.

Caselli, F. and Coleman, W. J. (2001). Cross-country technology diffusion: The case of computers. *American Economic Review*, 91(2):328–335.

Chokshi, A., DallaPiazza, M., Zhang, W. W., and Sifri, Z. (2021). Proximity to international airports and early transmission of covid-19 in the united states: An epidemiological assessment of the geographic distribution of 490,000 cases. *Travel Medicine and Infectious Disease*, 40:102004.

Comin, D. and Hobijn, B. (2004). Cross-country technology adoption: Making the theories face the facts. *Journal of Monetary Economics*, 51(1):39–83.

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in ghana. *American Economic Review*, 100(1):35–69.

Demirgüç-Kunt, A., Klapper, L., Singer, D., and Ansar, S. (2022). *The global findex database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. World Bank Publications.

Foster, A. D. and Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review of Economics*, 2(1):395–424.

Fu, J. and Mishra, M. (2022). Fintech in the time of covid- 19: Technological adoption during crises. *Journal of Financial Intermediation*, 50:100945.

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., et al. (2021). A global panel database of pandemic policies (oxford covid-19 government response tracker). *Nature Human Behaviour*, 5(4):529–538.

Hashim, H. T., Rassoul, E., El Abed, A., Bchara, J., Ahmadi, A., and Lucero-Prisno, D. E. (2022). Covid-19 denial in turkmenistan veiling the real situation. *Archives of Public Health*, 80(1):1–4.

Kaufmann, D., Kraay, A., and Mastruzzi, M. (2011). The worldwide governance indicators: Methodology and analytical issues1. *Hague Journal on the Rule of Law*, 3(2):220–246.

Khera, P., Ng, M. S. Y., Ogawa, M. S., and Sahay, M. R. (2021). Is digital financial inclusion unlocking growth? *IMF Working Papers*, (167):1– 30.

Mathieu, E., Ritchie, H., Rodés-Guirao, L., Appel, C., Giattino, C., Hasell, J., Macdonald, B., Dattani, S., Beltekian, D., Ortiz-Ospina, E., and Roser, M. (2020). Coronavirus pandemic (covid-19). *Our World in Data*. https://ourworldindata.org/coronavirus.

Nelson, R. R. and Phelps, E. S. (1966). Investment in humans, technological diffusion, and economic growth. *The American Economic Review*, 56(1/2):69–75.

Oster, E. and Thornton, R. (2012). Determinants of technology adoption: Peer effects in menstrual cup take-up. *Journal of the European Economic Association*, 10(6):1263–1293.

Passarelli, M., Bongiorno, G., Cucino, V., and Cariola, A. (2023). Adopting new technologies during the crisis: An empirical analysis of agricultural sector. *Technological Forecasting and Social Change*, 186(Part A):1–13.

Pelham, B. (2017). *Medieval ingenuity in fourteenth century english milling in middlesex, norfolk, and northumberland counties*. PhD thesis, University of Central Florida.

Riley, E. (2022). Resisting social pressure in the household using mobile money: Experimental evidence on microenterprise investment in uganda. *CSAE Working Paper Series*, 04:1–85.

Riom, C. and Valero, A. (2020). The business response to Covid-19: the CEP-CBI survey on technology adoption. Cep covid-19 analyses, Centre for Economic Performance, LSE.

Ripberger, J. T. (2011). Capturing curiosity: Using internet search trends to measure public attentiveness. *Policy Studies Journal*, 39(2):239–259.

Rosenberg, N. (1972). Factors affecting the diffusion of technology. *Explorations in Economic History*, (1):3–33.

Saka, O., Eichengreen, B., and Aksoy, C. G. (2022). Epidemic exposure, financial technology, and the digital divide. *Journal of Money, Credit and Banking*, 54(7):1913–1940.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1):159–209.

Tok, Y. W. and Heng, D. (2022). Fintech: Financial inclusion or exclusion? *IMF Working Papers*, (080):1– 35.

Valero, A. and Reenen, J. V. (2021). How is Covid-19 affecting firms' adoption of new technologies? *Economics Observatory*. https://www.economicsobservatory.com/how-covid-19-affecting-firms-adoption-new-technologies.

WHO (2022). Mental health and covid-19: Early evidence of the pandemic's impact: scientific brief. Technical report, World Health Organization.