Digitization and Inequality: A Theoretical Model of Skill-Based Access

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Abstract

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Digital transactions are becoming an increasingly common medium of exchange in everyday life. However, their impact on income inequality remains insufficiently understood. The purpose of this paper is to investigate the relationship between the digitization of the economy and income inequality across heterogeneous agents differentiated by skill. We propose an income-digitization model that expresses income inequality as a function of two parameters: the level of digitization in the economy, characterized by internet penetration, and the effort cost associated with digital participation, which depends on agents' education levels. A theoretical model is developed to examine how these factors interact to shape both intra- and inter-skill group income distributions. Using the concept of Lorenz Dominance, the model compares pre- and post-digitization income to assess shifts in inequality, and we use simulation to understand the implications from the theoretical exercise. As digitization expands, the results suggest that inequality is reduced among the low-skilled group, but it increases between the low- and high-skilled groups. However, the threshold for digital participation declines, lowering the effective effort cost and enabling broader inclusion. This effect is further amplified by a targeted policy intervention in the form of a subsidy, which reduces the effort cost by between 7.89% and 11.32% across increasing levels of digitization. The results highlight the role of the monopoly government in reducing exclusion for low-skilled agents.

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As a final concluding remark, I would like to end with the following quote:

> *"What we observe is not nature itself, but nature exposed to our method of questioning."* — Werner Heisenberg

Our economic realities are shaped by the frameworks and assumptions we choose. This perspective has helped shape how I approached the questions in my thesis — with humility, curiosity, and an awareness of the limitations inherent in economic modeling.

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1 Introduction

The growing prevalence of digital transactions has transformed the way individuals and businesses engage with the economy. As financial systems become increasingly digitized with global digital banking users projected to rise from 2.4 billion in 2020 to 3.6 billion by 2024, questions arise regarding the inclusivity and distributive effects of such changes. While digital technologies are often observed for their potential to promote financial inclusion by streamlining transactions and expanding access to services, their broader implications for income inequality remain underexplored.

Prior studies have focused on digital finance as a tool for inclusion, but few have modeled its heterogeneous impact on different skill groups within a general equilibrium setting. Moreover, access to the digital economy is not evenly distributed across or within countries (Qiang et al. 2024), and yet the impact on inequality is yet to be fully understood. Digital inequality arises not only from unequal access to ICT infrastructure, especially across the socio-economic spectrum, but also from disparities in digital literacy and engagement (Ferreira et al. 2021; Hargittai 2015). While some groups, such as the elderly or marginalized populations, struggle with digital skills or face structural barriers, others are better positioned to benefit from technological advancements (Vassilakopoulou and Hustad 2023). In this paper, the terms digital payments and digital economy are used interchangeably, as digital payment adoption often serves as an entry point into broader participation within the digital economy (Van Dinh 2024).

We develop a theoretical model to understand how digitization affects income distribution within and between skill groups, and to examine how digital subsidy can mitigate resulting inequalities. Income of agents is modeled as a function of two parameters: effort cost and the level of digitization within the economy. Effort cost is defined by individual skill, which is assumed to reflect the agent's level of education. Digitization is characterized by internet penetration, as internet access is a prerequisite for engaging in any form of digital exchange. Lastly, income inequality is analyzed using Lorenz dominance, comparing pre- and post-digitization income distributions.

We examine the impact of digitization on income inequality across skill levels by proposing a Two-Type model, later extended to a Continuum-Type framework, from which equilibrium conditions are derived. In a two-type model, agents are categorized into low- and high-skilled, establishing their utility function and decision rule. In contrast, the Continuum-Type model describes agents along a continuous skill spectrum. The characterization of equilibrium is subsequently established where a threshold emerges that determines whether agents self-select into accessing the digital economy, depending on the degree of digitization.

By modeling access thresholds and simulating effort cost reduction, this thesis contributes to the growing literature on digital inclusion by explicitly linking digitization to income inequality through agent skill heterogeneity.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature; Section 3 introduces the theoretical framework; Section 4 develops the model; Section 5 outlines the methodology; Section 6 presents the results; and Section 7 concludes the paper.

2 Literature Review

Globally, there is a transition from cash payments into digital payments, representing one of the most significant financial and digital transformations of our time. In 2020, approximately 2.4 billion people globally used digital banking, with this figure projected to rise to 3.6 billion within the next four years (Jadil, Rana, and Dwivedi 2021). The importance of digital payments lies in advantages of payment convenience as well as reduction in corruption in developing countries. Due to the traceability and removed human intermediaries, Setor, Senyo, and Addo (2021) suggested that digital transactions reduce corruption in 111 developing countries from 2010-2018. This raises the implications of the shift on digital and wealth inequality, rendering a crucial area of study. First, it is essential to define digital inequality and understand its significance. Second, it is important to identify the demographic groups most affected by it. This raises the question whether digital inequality contributes to wealth inequality. As a result, the present paper aims to examine various research findings on how digitization of the economy affect wealth inequality, as well as based on level of investment in Information Communication Technology (ICT).

Digital inequality generally arises from social, economic, and institutional factors; however, it can be categorized into two broad aspects. The first aspects of the digital divide relates to the issue of access to the internet and the various ICT. It was first associated with a socio-economic gap between those who have access to the computer and internet, and those who do not (Ferreira et al. 2021). This is supported by OECD definition, where they define it as a "gap between individuals, households, businesses and geographic areas at different socio-economic levels with regard both to their opportunities to access ICTs and to their use of the Internet for a wide variety of activities." (OECD, 2011) Beyond socio-economic factors, first-level divide also extends to spatial disparities. Studies have shown that information coverage and technological adoption are unevenly distributed, leading to the emergence of "digital oases" (high-access areas) and "digital deserts" (low-access areas), particularly in Sub-Saharan Africa, where access correlates strongly with economic strength

(Ferreira et al. 2021).

However, recent studies recognize that the digital divide extends beyond access, incorporating new trends and technologies. This leads to the second aspect of digital divide, which refers to inequality in digital literacy. While individuals from different socio-economic backgrounds may have equal access to the internet, not everyone possesses the same level of digital literacy to utilize it effectively. Due to these disparities in skills and knowledge, some individuals benefit from technological advancements more than others (Hargittai 2015). Two of the largest demographic groups affected by the second aspect digital divide are the elderly population and marginalized groups. Many older adults struggle to familiarize themselves with digital tools and services. While they commonly use smartphones for email and web browsing, few rely on them to access public services (Vassilakopoulou and Hustad 2023). As for marginalized population, such as refugees and immigrants, the language, resource limitation, and cost act as barriers to digital inclusion. Additionally, rural digital exclusion exist in three layers: availability, adoption and digital engagement. Notably, availability alone is not the most crucial factor for digital inclusion. Studies have shown that the presence of Internet Service Providers (ISPs) has little impact on internet adoption, which is instead driven primarily by differences in household attributes (Ma and Huang 2015).

Frost, Gambacorta, and Gambacorta (2022) utilized data from the Bank of Italy's Survey to examine the influence of financial development and technology on wealth inequality. Using an instrumental variable approach, specifically financial development in 1989 and internet access in a two-stage estimation, their findings indicate that financial development and technology positively affect financial wealth and returns. In particular, the wealthiest households benefited the most; however, the wealth gap narrowed as remote banking became more widespread. Additionally, the accessibility of remote banking is largely dependent on investment in ICT.

The rate of ICT adoption has been growing exponentially, yet economic growth remains relatively sluggish, where developed countries benefitted more from computing than developing countries (Stanley, Doucouliagos, and Steel 2018). Additionally, the progress of ICT adoption is not evenly distributed across regions. Developed countries have an 87% penetration rate, whereas developing countries lag behind at only 47% (Njangang et al. 2022). Regarding mobile phone subscriptions, adoption rates have reached saturation globally, with an average of 110.6 subscriptions per 100 people in 2023. However, this figure varies across countries, with some, such as Canada reporting lower rates, at 91.4 subscriptions per 100 people (Our World in Data 2023). This reflects that not all countries have full access to digital infrastructure, despite its growing importance for participating in digital transactions, even in advanced economies like Canada. Research suggests that ICT impact on wealth inequality is influenced by institutional factors, particularly democracy. Strengthening democratic institutions in both developed and developing countries serves as an effective mechanism for reducing ICT- driven disparities (Njangang et al. 2022). Furthermore, Njangang et al. (2022) argue that ICT is more likely to promote wealth accumulation in developed countries, widening the income gap between developed and developing countries.

Existing literature studying on the impact of the digital economy on income distribution has made divergent conclusions (Liang et al. 2025). Some studies support the notion that ICT reduces income disparities, while others suggest it exacerbates inequality. Richmond and Triplett (2018) explored the impact of ICT on income inequality across different countries. Utilizing data from 109 countries between 2001 and 2014, their study evaluated the relative magnitude of ICT's impact compared to traditional economic infrastructure. The results suggest that the effect of ICT on income inequality varies depending on the type of ICT and the measure of inequality used. Moreover, their findings highlight the interplay between ICT, economic conditions, and political factors, underscoring the need for policy interventions to ensure equitable access for all.

To further examine the relationship between digital finance and income inequality, Yao and Ma (2022) analyzed data from 280 Chinese cities between 2011 and 2020. Employing both linear and nonlinear models, their results reveal evidence of a Kuznets effect, which follows a bell-shaped relationship. In the early stages, as digital finance expands, inequality increases, because wealthier individuals and businesses have better access to technology and financial services, benefiting more than lower-income groups. However, as digital finance becomes more widespread, this trend reverses, and income inequality begins to decline as more low-income individuals gain access to digital financial services, improving financial inclusion. In summary, the Kuznets effect suggests that digital finance initially exacerbates income inequality before ultimately reducing it as regional economic levels rise. This is evident where most Chinese regions are still experiencing widening income inequality due to digital finance development, though this trend is expected to reverse with further economic advancement.

Nevertheless, the digital economy has been found to increase skill-biased inequality, disproportionately favoring high-skilled over low-skilled labor (Yang, Yao, and Dong 2023). Yin and Choi (2023) provide evidence that ICT contributes to narrowing income disparities globally. Additionally, ICT has been found to reduce the urban-rural income gap in developed countries (Braesemann, Lehdonvirta, and Kässi 2022), while inclusive digital finance plays a crucial role in reducing urban-rural income disparities (Liu, Zhang, and Zhou 2023).

The 2016 Indian demonetization event serves as a quasi-natural experiment on the rapid adoption of digital payment technology. Crouzet, Gupta, and Mezzanotti (2023) investigate how coordination frictions impact technology adoption during this event, which caused a significant shock to cash availability. Their findings suggest that demonetization led to a persistent increase in the use of electronic wallets, particularly in areas more affected by cash shortages. Model estimates indicate that the adoption rate would have been 45% lower without complementary measures. Similarly, Chodorow-Reich et al. (2020) examined the 2016 Indian demonetization using a model in which cash is held for transactions and tax evasion. Testing their model across various Indian districts with different datasets, their findings suggest that demonetization resulted in reduced economic activity, accelerated adoption of digital payments, and a decline in bank credit growth. These effects led to a temporary 2% contraction in employment and output, ultimately challenging the notion of monetary neutrality and offering insights on its consequential inequality.

Given these findings, it is essential to consider an economic model that connects income inequality with skill disparities underlying the digital divide. Accordingly, we will introduce a model to examine the relationship between digitization and income inequality.

3 Income-Digitization Model

This section introduces the theoretical framework used to examine the distributional effects of digitization. The model begins with a two-type agent specification, distinguishing between low-skilled and high-skilled individuals. It is then extended to a continuum-type agent setting, where agents are distributed along a continuous skill spectrum. This layered approach enables both analytical tractability and a more comprehensive view of how digitization interacts with heterogeneity in skills. Subsequently, the model characterizes the equilibrium and identifies the threshold at which agents self-select into digital participation.

3.1 Economic Environment

In this economic environment, the government acts as a monopoly provider of two services: a non-digital service and a digital service. The digital service offers additional benefits, which may arise from a reduction in transaction costs or from improved access to services that were hitherto inaccessible. This effect is modeled by assuming that access to digital services enhances income through a function λ where $0 < \lambda < 1$. It is further assumed that access to digital service allow for access to digital finance.

The rate of return to one unit of expenditure on the non-digital service is normalized to 1.

$$\hat{l} := 1 \tag{1}$$

In contrast, the rate of return for the digital service is expressed as

$$\hat{h} := 1 + \lambda \tag{2}$$

where Equation (2) captures the additional benefit provided by digital services relative to the non-digital service, as expressed in Equation (1).

3.2 Two-Type Model

Consider a continuum of agents indexed by $i \in [0, 1]$, with unit measure of 1. Each agent is characterized by a type $\theta_i \in \{L, H\}$, where L and H is categorized as low- and high-skilled, respectively, and that $0 < L < H < 1$. Agents of type L earn income x_L, while agents of type H earn x_H, with $x_L < x_H$.

Following digitization, income for any agent becomes subject to a multiplicative gain. Specifically, for any income level x, the digitized income is $(1 + \lambda)x$, where $\lambda \in (0, 1)$ represents the digital amplification factor.

To obtain income, each agent exerts effort, e, which incurs a cost given by $-\frac{e}{\theta_i}$. Thus, the cost of effort is inversely related to the agent's type, implying that higher-type agents face a lower marginal cost of effort.

In addition, effort e is normalized to reflect the education level of each agent, with $e \in [0, 1]$.

In terms of agents' utility, we will assume that they derive utility from their income. For a low-skilled agent, the utility derived from consuming the non-digital service, $\hat{l}$, is

$$x_L, \tag{3}$$

while the utility from consuming the digital service, $\hat{h}$, is

$$x_L(1 + \lambda) - \frac{e}{L}. \tag{4}$$

A low-skilled worker will prefer $\hat{l}$ over $\hat{h}$ if

$$x_L > (1 + \lambda)x_L - \frac{e}{L}, \tag{5}$$

which rearranges to the condition

$$\frac{e}{L} > \lambda x_L. \tag{6}$$

For a high-skilled agent, the payoff from consuming $\hat{l}$ is

$$x_H, \tag{7}$$

and the payoff from the $\hat{h}$ is

$$(1+\lambda)x_H - \frac{e}{H}. \tag{8}$$

The agent prefers the $\hat{h}$ if

$$(1+\lambda)x_H - \frac{e}{H} > x_H, \tag{9}$$

which simplifies to

$$\lambda x_H > \frac{e}{H}. \tag{10}$$

3.3 Continuum-Type Model

Let agent type θ be drawn from the compact interval $[0, 1] \subseteq \mathcal{G}$, where $\mathcal{G}$ denotes the full set of agents. Each agent's income is determined by a strictly increasing and convex production function

$$y = h(\theta), \tag{11}$$

which maps their type to income. The function $h(\cdot)$ satisfies the following properties: it is anchored at the origin such that

$$h(0) = 0; \tag{12}$$

it is strictly increasing with

$$h'(\theta) > 0, \tag{13}$$

and strictly convex with

$$h''(\theta) > 0 \quad \text{for all } \theta \in (0, 1); \tag{14}$$

and the marginal return becomes unbounded as type approaches the upper bound, i.e.,

$$\lim_{\theta \to 1} h'(\theta) = \infty. \tag{15}$$

These properties imply that income rises at an accelerating rate with respect to type, capturing increasing returns to ability.

Lastly, we express the pre-digitization utility as

$$x_\theta, \tag{16}$$

and the post-digitization utility as

$$(1+\lambda)x_\theta - \frac{e}{\theta}. \tag{17}$$

3.4 Threshold Equilibrium

In equilibrium, there exist a continuum of agents where we can rewrite Equation (5) and Equation (9) to characterize the decision rule for digital participation as:

$$h(\theta') > (1+\lambda)h(\theta') - \frac{e}{\theta'} \tag{18}$$

$$(1+\lambda)h(\theta) - \frac{e}{\theta} > h(\theta) \tag{19}$$

Equations (18)and (19) describe the participation threshold for a continuum of agents deciding between $\hat{l}$ and $\hat{h}$, respectively. These inequalities define the conditions under which an agent prefers one mode over the other.

To identify the equilibrium threshold θ^*, we solve endogenously for the point at which agents are indifferent between digital and non-digital participation. This occurs at the break-even point where both payoffs are equal:

$$(1+\lambda)h(\theta^*) - \frac{e}{\theta^*} = h(\theta^*) \tag{20}$$

Rearranging Equation (20), we obtain the threshold condition:

$$\theta^* h(\theta^*) = \frac{e}{\lambda} \tag{21}$$

Redefining Equation (21) as a function $f(\theta)$

$$f(\theta) = \begin{cases} \theta h(\theta) - \dfrac{e}{\lambda}, & \text{if } \theta > 0 \\ -\dfrac{e}{\lambda}, & \text{if } \theta = 0 \end{cases} \tag{22}$$

Since $f(\theta)$ is continuous, we have $f(0) = -\frac{e}{\lambda} < 0$, and under the assumption that

$f(\theta^*) = \theta^* h(\theta^*) - \frac{e}{\lambda} > 0$ for some $\theta^* > 0$, it follows by the Intermediate Value Theorem that there exists a solution $\theta^* \in (0, \hat{\theta})$ such that Equation 21 is satisfied.

The value θ^* defines the equilibrium threshold at which agents are indifferent between participating and not participating in the digital economy, thereby completing the model's characterization of threshold equilibrium. Agents with skill levels above θ^* will self-select into digital participation, while those with skill levels below θ^* will opt out.

4 Analysis

In this analysis, we first outline how income inequality is assessed, followed by a specification of the income of our agents.

Several measures have been proposed to quantify inequality, though few provide a comprehensive assessment. One of the simplest is the range, which captures the difference between the richest and poorest individuals. While this measure is intuitive and easy to compute, it is limited in scope, as it ignores the distribution of income among the rest of the population.

A more informative method examines how far each individual's income deviates from the mean, a concept known as the mean deviation. This is calculated by taking the absolute differences between each individual's income and the average income, and then summing these deviations. Unlike the range, the mean deviation reflects the distribution across all individuals, providing a more accurate picture of inequality.

To further improve upon these measures, the Lorenz curve is introduced. It provides a graphical representation of the cumulative distribution of income or wealth, making it a widely used tool for visualizing inequality. Lorenz dominance builds on this concept by enabling comparisons between distributions; it provides a formal condition under which one distribution is considered more unequal than another.

Finally, the analysis considers two types of agent specifications: discrete and continuous. In the discrete setting, agents are categorized as either low-skilled or high-skilled. In the continuous setting, agents are represented along a skill continuum, allowing for an infinite number of types. Both formulations are essential for understanding equilibrium behavior and the distributional implications of digitization in the economy.

4.1 Lorenz Curve

The Lorenz Curve is constructed by ranking agents from poorest to richest based on the cumulative percentage of the population, and plotting the cumulative percentage of total income (or wealth) held by the bottom p percent of the population.

Mathematically, if $x = (x_1, x_2, \ldots, x_n)$ represents the income distribution of a population, then the Lorenz curve is given by:

$$L(p) = \frac{\sum_{i=1}^{p} y_i}{\sum_{i=1}^{n} y_i} \tag{23}$$

where p denotes the proportion of the population under consideration.

A perfectly equal society is denoted by a diagonal line starting from the origin, where each proportion of the population holds exactly the same proportion of income. For example, the bottom 10% of the people would hold 10% of total income, the subsequent 20% of the population holds exactly 20%, and so on. The further the Lorenz curve deviates from this line, the more unequal the distribution. This is shown in Figure 1.

4.2 Lorenz Dominance

Extending from the Lorenz curve, Lorenz dominance provides a partial ordering of inequality. The formal definition of Lorenz dominance follows the approach of Myles (1995).

Given two income distributions x and y, it can be said that x *Lorenz-dominates* y if the Lorenz curve of x is always above or equal to that of y, meaning that at every percentile, the cumulative share of income in x is at least as large as in y.

Formally,

$$x \succeq_{LD} y \quad \text{if} \quad L_x(p) \geq L_y(p) \quad \forall p \in [0, 1] \tag{24}$$

where $L_x(p)$ and $L_y(p)$ are the Lorenz curves of distributions x and y, respectively. If x Lorenz-dominates y, then distribution x is considered less unequal than y. However, if the Lorenz curves cross each other, then Lorenz dominance cannot determine which distribution is more unequal, highlighting its incompleteness as a ranking method. This is shown in Figure 2a and Figure 2b.

The argument for Lorenz dominance is as follows by considering two income distributions

$$\mathbf{x} = (x_1, x_2, \ldots, x_n) \quad \text{and} \quad \mathbf{y} = (y_1, y_2, \ldots, y_n) \tag{25}$$

such that both distributions have the same total income:

$$\sum_{i=1}^{n} x_i = \sum_{i=1}^{n} y_i. \tag{26}$$

Now, construct permuted versions of these distributions, denoted as $\mathbf{x}'$ and $\mathbf{y}'$, which are sorted in non-decreasing order:

$$x'_i \leq x'_{i+1}, \quad y'_i \leq y'_{i+1} \quad \forall i. \tag{27}$$

Define m as the largest index such that $x_m \neq y_m$. If for all $i < m$, we have:

$$x'_i \geq y'_i, \tag{28}$$

then the reordered distribution $\mathbf{x}'$ is at least as equal as $\mathbf{y}'$, meaning:

$$\mathbf{x}' \preceq_{LD} \mathbf{y}'. \tag{29}$$

By symmetry, since $\mathbf{x}$ and $\mathbf{x}'$ are equivalent, and $\mathbf{y}$ and $\mathbf{y}'$ are equivalent, we conclude:

$$\mathbf{x} \simeq \mathbf{x}' \quad \text{and} \quad \mathbf{y} \simeq \mathbf{y}' \quad \Rightarrow \quad \mathbf{x} \preceq_{LD} \mathbf{y}. \tag{30}$$

Furthermore, if $\mathbf{x}' \preceq_{LD} \mathbf{y}'$, then this means that $\mathbf{x}'$ must lie entirely on or above $\mathbf{y}'$. This means that for every percentile of the population, the cumulative income in $\mathbf{x}'$ is at least as high as in $\mathbf{y}'$, indicating a distribution that is more equal.

4.3 Income Specification

Given the assumption that income is derived from utility, we specify the agent's pre-digitization income as

$$y_\theta \tag{31}$$

where y_θ denotes baseline income prior to digital engagement, and $\theta \in [L, H]$ represents the agent's type, capturing their skill level.

If the agent chooses to participate in the digital economy, their income becomes:

$$y(\theta, \lambda) = y_\theta \cdot (1 + \lambda) - \frac{e}{\theta} \tag{32}$$

Here, $\lambda \in (0, 1)$ is the digitization parameter capturing income amplification, and $\frac{e}{\theta}$ reflects the effort cost, which varies inversely with the agent's type.

The concept of Lorenz curve and Lorenz Dominance is applied to Equations 31 and 32 to assess how digitization alters the distribution of income and affects overall inequality. By plotting the cumulative share of income earned by the population, both before and after digitization, the Lorenz curve offers a graphical representation of inequality. Lorenz dominance is then used to formally compare the two distributions: if the post-digitization Lorenz curve lies entirely below the pre-digitization curve, this indicates an unambiguous increase in inequality after digitization. Conversely, if the curve shifts upward, it implies a more equitable income distribution. This analytical approach allows us to evaluate whether digital transformation exacerbates or mitigates disparities across agent types.

4.4 Comparative Statics

We define post-digitization income as a function of type θ and digitization level λ in Equation 32. To understand how digitization affects income, we examine the first and second derivatives of this expression with respect to λ.

First-Order Condition:

$$\frac{\partial y}{\partial \lambda} = y_\theta > 0 \tag{33}$$

This first-order condition implies that marginal effect of digitization on income is strictly positive for all $\lambda > 0$. In other words, increasing the level of digitization λ raises income for any agent of type θ. This reflects the idea that digital access improves productivity, yielding income gains even for small increases in λ. The magnitude of this gain, however, is constant due to the functional form.

Second-Order Condition:

$$\frac{\partial^2 y}{\partial \lambda^2} = 0 \tag{34}$$

The second-order condition yields zero, indicating that the rate of change in marginal effect of digitization on income remains constant across all values of λ. This condition from our model suggests that relationship between digitization and income is linear. While linearity enhances tractability, it is important to note that it abstracts from possible increasing returns to digitization observed in high technology as noted by Arthur (1996).

Overall, the first- and second-order conditions illustrate the effects of digitization on income under a linear specification. While stylized, this approach captures the fundamental insight into the relationship between digital adoption and skill-based income variation.

5 Methodology

5.1 Income Transformation and Simulation Procedure

This paper employs a simulation approach to understand the effects of digitization on income, calibrated using values extracted from the World Bank. We use the World Bank standard for duration of education, and also sourced internet penetration rates based on countries.

To simulate the income-digitization impact, we define post-digitization income using Equation 32. The digitization effect is captured through the transformation term $(1 + \lambda)$, ensuring that the marginal benefit of digital engagement scales proportionally with income.

The post-digitization income for low- and high-skilled agents is computed as:

$$y'_\theta = \max\left((1+\lambda)\cdot y_\theta - \frac{e}{\theta},\ \varepsilon\right) \tag{35}$$

where $\varepsilon = 10^{-4}$ serves as a lower bound to avoid negative or zero income values. The max function is used to also ensure that post-digitization income remains non-negative.

A study conducted by Lopez and Servén (2006) has shown that the income per capita distributed is approximated empirically by a log-normal distribution. As a result, the pre-digitization income distribution is simulated from a log-normal distribution, calibrated to match the average pre-digitization levels y_L and y_H. Specifically, the parameters are set as:

$$\mu_L = \log(y_L) - 0.5, \quad \mu_H = \log(y_H) - 0.5, \quad \sigma = 0.5 \tag{36}$$

to generate income distributions with empirically plausible right skew. Each group's incomes are then rescaled so that the sample means match the intended y_L and y_H levels before applying the post-digitization transformation.

A standard deviation of $\sigma = 0.5$ is commonly used in economic simulation to capture the right-skewed nature of log-normal distribution. For example, Fair (2016) model agent heterogeneity using a $\sigma = 0.5$ for log-normal distribution for ability. While it was used for ability, the choice to use $\sigma = 0.5$ remains relevant for income. Fair (2016) uses ability to translate into earnings, therefore this paper will follow its approach in using $\sigma = 0.5$ to capture empirically realistic variation in income, while avoiding an extreme tail behavior.

To compare the effects of income before and after digitization, Lorenz curves were constructed using Equation 31 and Equation 35, in order to understand the income inequality. The simulation was conducted with MATLAB.

In addition to inequality analysis, threshold equilibrium is estimated using Equation 21. Through this estimation, it shows us the necessary level of education for self-selection into the digital economy.

Lastly, this paper explores the role of policy intervention in the form of a subsidy for e, with the aim of assessing its potential to influence participation thresholds.

5.2 Calibration

Model parameters were calibrated using both empirical benchmarks and theoretical considerations to ensure realism and internal consistency. The simulation assumes a population of $n = 10{,}000$ agents. A large sample size ensures smoother Lorenz curves and more accurate approximations of theoretical distributions, particularly when modeling inequality.

To reflect real-world labor force composition, we assume that 70% of agents are low-skilled. This assumption is consistent with data from real-world, which reports that over 60% of the global employed population operates within the informal economy (International Labour Organization 2023). Skewing the agent population toward lower-skilled individuals allows the simulation to capture more realistic income distributions and better reflect observed inequality patterns.

Baseline incomes are set at $y_H = 5$ and $y_L = 2$, implying that high-skilled agents earn 2.5 times more than their low-skilled counterparts. This calibration is motivated by the empirical findings of Montenegro and Patrinos (2014), who document average returns to education of roughly 10% for primary schooling and 16% for tertiary education. Given the typical years of schooling associated with each education level, a 2.5:1 income ratio offers a plausible approximation of observed earnings gaps across skill types.

Effort, denoted by e, represents the minimum educational threshold required to effectively engage with digital services. Based on World Bank (2025c, 2025a, 2025d), the standard duration of formal education consists of approximately 6 years of primary, followed by 3 years each of lower and upper secondary schooling. Therefore, we assume that a full educational pathway spans approximately 20 year, from primary school to doctoral-level education. Furthermore, we assume that digital literacy requires completion of secondary education (12 years), and therefore normalize effort as $e = 0.6$. Detailed mappings of education levels and effort values are presented in Table 1 in Appendix B.

Digitization is represented by the parameter λ, which we interpret as the proportion of the population with internet access. A higher λ reflects broader digital connectivity, enhancing the productivity and economic value of digital tools through network effects and greater market participation. As more individuals gain internet access, the potential returns to adopting digital technologies increase, amplifying the income-enhancing effect of digitization. Internet penetration serves as a reasonable proxy for digital adoption, as access to the internet is a prerequisite for using most digital financial services. We explore several values of $\lambda \in \{0.25, 0.5, 0.75, 0.99\}$ to simulate varying stages of digital development. The upper bound $\lambda = 0.99$ reflects a highly digitized society, without assuming full saturation. Further details on this calibration are provided in Appendix B, Table 2.

Agent types are further differentiated by their skill levels, represented by θ. We assign $\theta = 0.3$ to low-skilled agents with only primary education (6 years) and $\theta = 0.8$ to high-skilled agents with 16 years of schooling, corresponding to college completion. These values are normalized by the 20-year education scale described above and are reported in Table 1.

Finally, the simulation includes a digital access subsidy, denoted by $-e$, which is interpreted as a policy intervention by a monopoly government aimed at reducing the cost of adopting digital tools. In this setup, a fixed subsidy of -0.2 is assumed, reflecting partial public investment in digital training or infrastructure.

6 Results

6.1 Income Inequality Analysis

The simulations are conducted for varying levels of digitization, $\lambda \in \{0.25, 0.5, 0.75, 0.99\}$, as shown in Figure 3. While the model assumes that individuals choose whether to adopt digital technologies based on income maximization, the simulation reflects a more realistic institutional environment where digital adoption is increasingly compulsory rather than optional.

In practice, individuals, particularly low-skilled, often face situations where the cost of non-adoptions is high enough to prohibit digital access. This limit their access to essential services, employment platforms, or even identity verification (e.g, two-factor authentication), all of which are necessary to require engagement with digital tools. As noted by Warschauer (2004), digital exclusion is also further exacerbated by institutional pressure, where digital systems become default channels for communications, services and transactions. In such scenarios, the inability to use these technologies effectively may lead to relative marginalization or income loss. Therefore, the simulation assumes universal adoption of new technologies, irrespective of skill levels.

The resulting Lorenz curves reveal asymmetrical effects on income distribution both within and between skill groups. Three key observations emerge: (1) the difference in inequality between low- and high-skilled agents; (2) the reduction in inequality within low-skill group as λ increases; and lastly, (3) the disproportionate exposure of the lowest-income individuals within the low-skilled group.

Firstly, comparing between the two skill groups, it is observed that high-skilled agents remain largely unaffected by digitization as λ increases. In contrast, low-skilled agents are penalized more severely due to their higher effort-cost factor, suggesting that the barrier to digital adoption is significantly higher for low-skilled agents relative to their counterparts.

Secondly, another observation noted is the decline of inequality within low-skilled group as λ increases. In Figure 3, approximately 50% of the low-skilled population earns near-zero income when $\lambda = 0.25$, with gains concentrated in the upper half of the distribution. This extreme compression implies that the cost burden disproportionately penalizes not only low-skilled agents overall but particularly those at the bottom of the income distribution. In Figure 3g, we observe that inequality has decreased, where an estimated 20% of the population earns near-zero income.

A possible explanation suggests that the increase in digitization and decrease in cost burden is due to the reduction in information asymmetries between buyers and sellers. By reducing the cost of acquiring information and enabling information more transparently available, digital technologies can make new transactions possible. This, in turn, saves on the cost of time, travel and effort, which are often significant burdens for low-income or remote individuals. Overall, increase in digitization enables a broader set of economic exchanges, particularly for individuals and firms previously excluded due to remoteness or lack of credibility signals (World Bank Group 2016). Nevertheless, although there is a reduction in inequality intra-group, post-digitization income still dominates pre-digitization income for low-skilled agents, leading the agents to self-select into the non-digitized group.

6.2 Equilibrium Analysis

In equilibrium, the model illustrates the threshold level of effort required where a continuum of agents self-select whether they choose to adopt digitization. Based on the equilibrium analysis, the cutoff point for self-selection decreases as digitization increases as shown in Figure 4. The numerical results are reported in Table 3.

In Figure 4a, $\lambda = 0.25$ and the corresponding effort is approximately 0.76, which is equivalent to a bachelor's graduate in our framework. As λ increases to full digitization, the effort decreases to approximately 0.5, totaling to less than a secondary graduate.

The observed decline in θ as digitization expands may also be attributed to economies of scale and network effects. This provides cost advantages for companies to gain leverage in digital leverage technologies to produce and distribute goods and services more efficiently at a larger volume (Dedola et al. 2023). In terms of digital finance, as more users adopt digital payments, service providers streamline processes, reducing the complexity in accessibility. Thus, digitization not only lowers individual effort cost, but it also systematically enables greater inclusion due to cost and design efficiencies (Klapper and Singer 2014).

6.3 Policy Analysis

For policy analysis, we assume a subsidy from the monopoly government that reduces the effort cost from $e = 0.6$ to $e = 0.4$. This adjustment perceives that lower secondary education becomes sufficient to fully access and benefit from the digital economy.

The results, summarized in Table 4, reveal an evident decrease in the threshold level θ^* across all levels of digitization. This reduction implies that a broader segment of the population, in particular, individuals with lower skills or education now finds digital participation worthwhile. Specifically, the effort cost required for digital adoption effectively decreases between 7.89% to 11.32%, as shown in Table 5. This suggests that even modest policy interventions can significantly lower the barrier to entry and promote more inclusive digital participation. Unlike supply-side interventions that raise λ by expanding digital infrastructure, subsidizing the effort cost e represents a demand-side approach that lowers barriers of entry for excluded agents.

In real-world terms, this policy could take the form of digital literacy training (San Andres and Hernando 2019), or financial assistance for mobile phone service (World Bank 2025e); each of which lowers the effective cost of digital entry. Ultimately, the results suggest that the monopoly government can play a role in reducing exclusion in a digitizing economy.

7 Conclusion

The findings of this study underscore the complex relationship between digitization and income inequality. As economies become increasingly digitized, digital transactions and participation expands, albeit at a disparate rate. Hence, we propose the income-digitization model, solve endogenously for a threshold equilibrium and analyze a policy subsidy.

The attractive feature of the income-digitization model is that it ties the level of digitization to income based on a linear relationship. Specifically, post-digitization income improves within low-skilled individuals, but the gap between low- and high-skilled agents persists. The results show that as internet penetration increases, the inequality inter-skill group (between low- and high-skill) increases, and that post-digitized income Lorenz dominates pre-digitized income for low-skilled agents. Despite widening inequality, the inequality intra-skill among low-skilled group decreases as digitization increases.

Moreover, as digitization becomes more accessible, the threshold for digital participation declines, indicating that broader digitization lowers the effective effort cost. This is further amplified by a subsidy provided by the monopoly government. Individuals who are previously excluded from the digital economy due to effort cost are more likely to participate as access improves.

Future work could extend the framework by incorporating curvature in income-digitization relationship. Other measures for digitization, more directly tied to digital transactions, could also be explored. Moreover, it would be valuable to validate the model's threshold based results against empirical data from countries exhibiting similar level of digitization.

These findings suggest that the distributional effects of digitization depend not only on infrastructure availability but also on the varying capacities of agents to engage with digital services. As such, the skill levels of heterogeneous agents play a significant role in determining their income outcomes within a digitizing economy.

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8 Appendix A: Figures

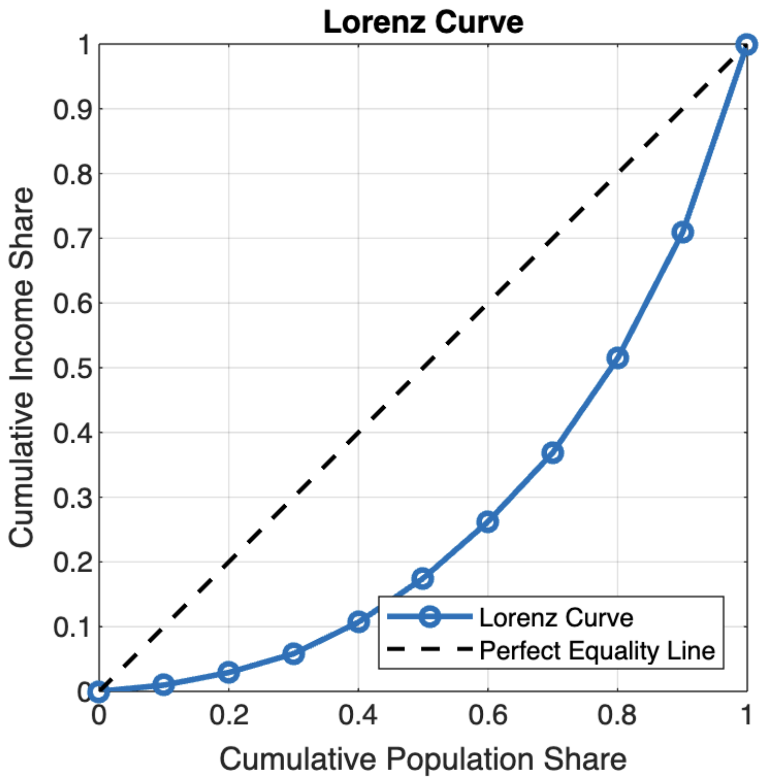
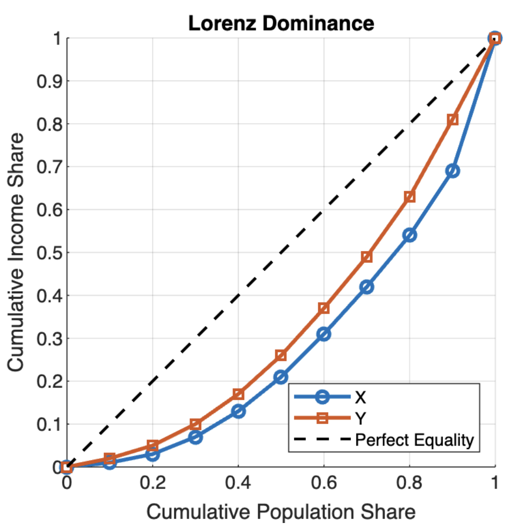
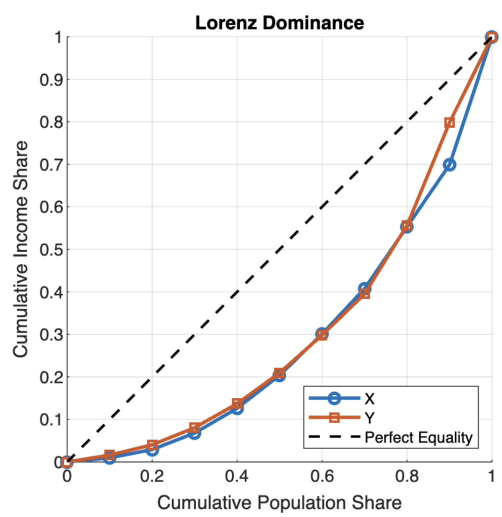


Figure 1: Illustration of Lorenz Curve

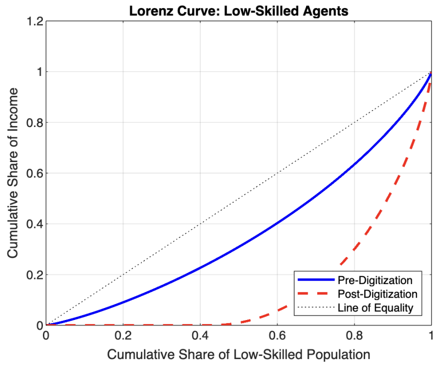


(a) Lorenz Dominance: X dominates Y

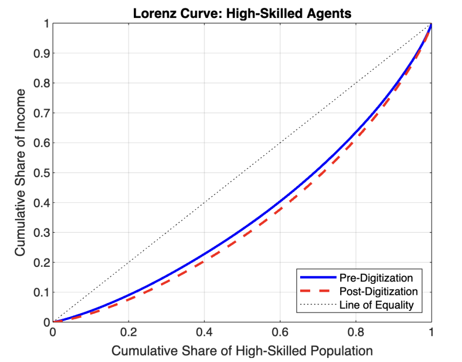


(b) Incomplete Dominance

Figure 2: Comparison of Lorenz Dominance (a) and Incomplete Dominance (b)

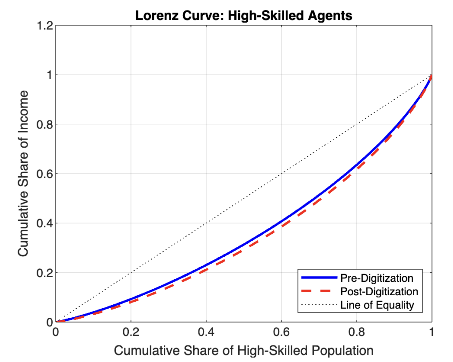


(a) Low-skilled, $\lambda = 0.25$

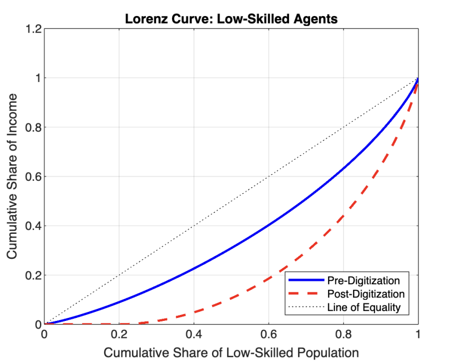


(b) High-skilled, $\lambda = 0.25$

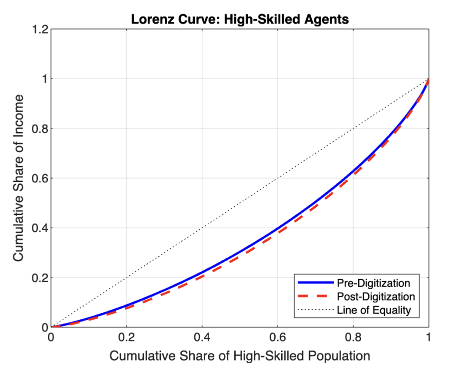
(c) Low-skilled, $\lambda = 0.50$



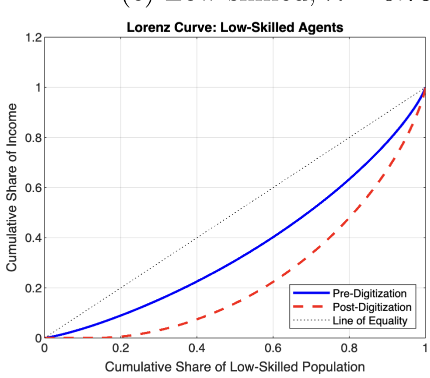
(d) High-skilled, $\lambda = 0.50$



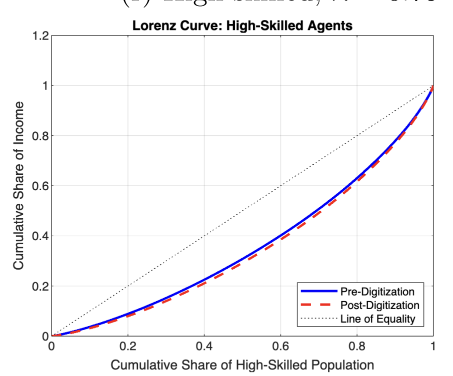
(e) Low-skilled, $\lambda = 0.75$



(f) High-skilled, $\lambda = 0.75$

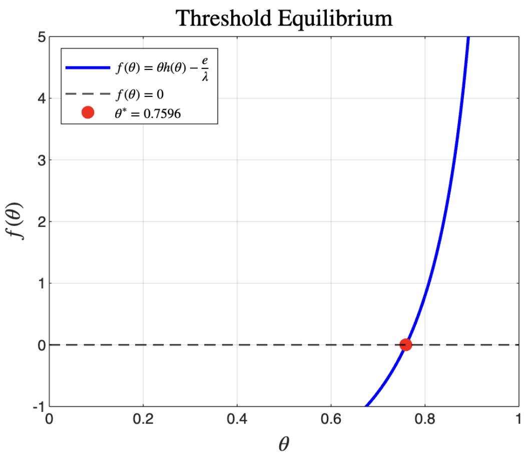


(g) Low-skilled, $\lambda = 0.99$

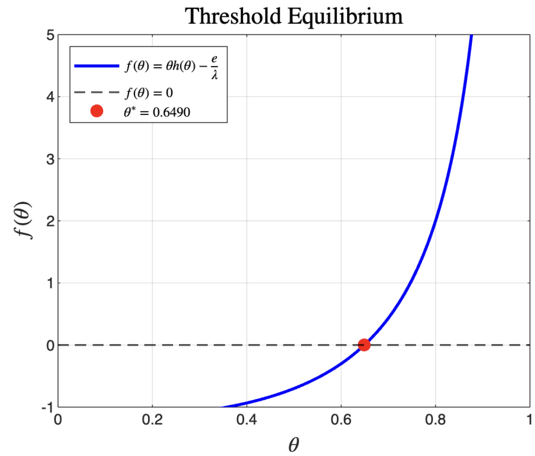


(h) High-skilled, $\lambda = 0.99$

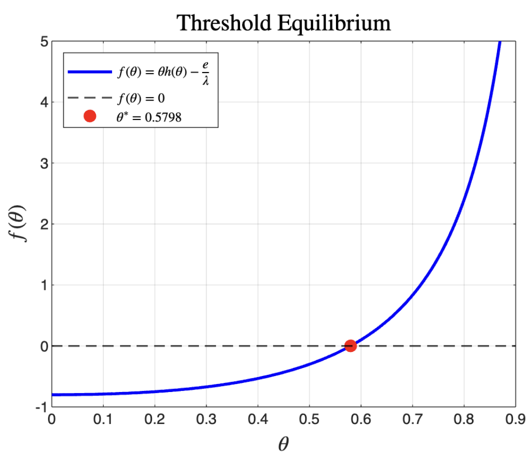
Figure 3: Lorenz curves for low- and high-skilled agents across different levels of digitization (λ).



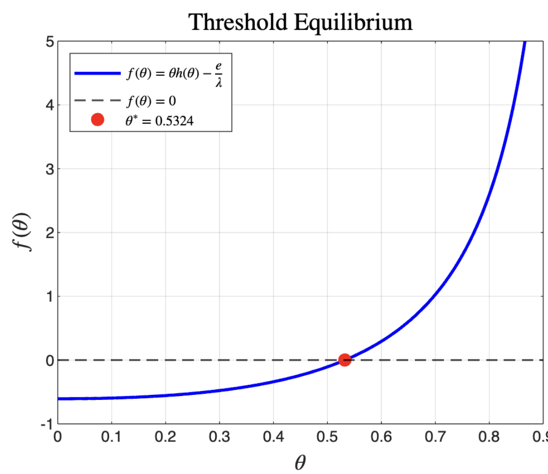
(a) $\lambda = 0.25$, $\theta^* = 0.76$



(b) $\lambda = 0.5$, $\theta^* = 0.65$



(c) $\lambda = 0.75$, $\theta^* = 0.58$



(d) $\lambda = 0.99$, $\theta^* = 0.53$

Figure 4: Threshold Equilibrium as Digitization Increases

9 Appendix B: Tables

Table 1: Normalization of educational attainment

Education Level	**Years of Education Completed**	**Normalized Value**
Primary	6	0.3
Secondary	12	0.6
Bachelors	16	0.8
Doctoral	20	1.0

Table 2: Internet penetration rates and corresponding normalized values

Internet Penetration (%)	**Normalized Value**
25	0.25
50	0.50
75	0.75
99	0.99
100	1.00

Table 3: Threshold levels across different levels of digitization

Digitization Level λ	**Threshold** θ^*
0.25	0.76
0.50	0.65
0.75	0.58
0.99	0.53

Table 4: Subsidized threshold levels across different levels of digitization

Digitization Level λ	**Threshold** θ^*
0.25	0.70
0.50	0.58
0.75	0.51
0.99	0.47

Table 5: Percentage reduction in participation threshold θ^* after policy intervention

Digitization Level λ	**Original Threshold** θ^*	**% Decrease**
0.25	$0.76 \rightarrow 0.70$	7.89%
0.50	$0.65 \rightarrow 0.58$	10.77%
0.75	$0.58 \rightarrow 0.51$	12.07%
0.99	$0.53 \rightarrow 0.47$	11.32%