BUFFERING OVERHEAD SHOCKS: HOW DIGITAL PAYMENTS MODERATE ENERGY COSTS AND LABOR PRODUCTIVITY IN INFORMAL ENTERPRISES IN CAMBODIA

Tung Nhu Nguyen [1,2]*

[1]Lecturer, School of Business, International University, Ho Chi Minh City, Vietnam; nntung@hcmiu.edu.vn
[2] Vietnam National University, Ho Chi Minh City, Vietnam
* Corresponding Author: nntung@hcmiu.edu.vn

Abstract
This study examines how digital money adoption affects labor productivity in Cambodian informal enterprises and whether digital tools moderate electricity overhead shocks. Using microdata from the World Bank's 2024 Cambodian Informal Sector Enterprise Survey across Phnom Penh, Battambang, Siem Reap, and Sihanoukville, we find that while computer adoption remains minimal (8.96%), digital payments via mobile devices such as mobile phones reach 55.77%. Instrumental variable (2SLS) estimates confirm that computer access boosts sales per worker, while positively moderates the relationship between electricity expenditure per worker and labor productivity. Digital payments act as working-capital liquidity buffers, enabling energy-intensive informal enterprises to sustain productive capacity and achieve higher labor productivity.

Keywords: digital money, mobile payments, labor productivity, electricity costs, informal enterprises, reverse causality, Two-Stage Least Squares (2SLS), Cambodia.

1. Introduction

1.1 Background

Informal enterprises constitute the structural backbone of economic activity across developing and emerging economies, particularly within Southeast Asia (Savuth & Oum, 2023). In Cambodia, the informal sector accounts for the vast majority of non-agricultural employment—estimated at roughly 88.3% of the active workforce (ILO, 2023). Ranging from urban street vendors and night-market stalls to small-scale service providers and family-run artisanal workshops, these micro-enterprises operate largely outside formal registration frameworks. Constrained by limited financial capital, poor record-keeping practices, and severe barriers to formal credit access, Cambodian informal firms face persistent labor productivity deficits that risk locking micro-entrepreneurs into low-income traps (Aberra et al., 2022; La Porta & Shleifer, 2014).

In recent years, Cambodia has experienced a rapid digital financial transformation that is reshaping traditional informal commerce. Historically dominated by physical cash transactions (Cambodian Riel and US Dollars), the commercial landscape has shifted significantly with the widespread adoption of mobile banking, QR-code payment networks, and interoperable digital settlement architectures such as the National Bank of Cambodia's Bakong platform (Savuth & Oum, 2023). Micro-level survey data show that over 55% of Cambodian informal micro-enterprises now use digital payments for daily commercial transactions. At the same time, urban informal enterprises face mounting operational challenges driven by high, volatile utility overheads, particularly electricity costs (Ankrah et al., 2023). As micro-firms extend operating hours, adopt powered appliances, or deploy refrigeration and machinery to scale up, energy overhead rapidly becomes a major fixed cash outflow.

Unlike formal corporations equipped with structured working-capital credit lines and automated energy management systems, cash-bound informal vendors must rely on real-time transactional liquidity to cushion operational cash drains. Digital payment adoption can accelerate cash conversion, minimize receivables delays, and eliminate cash-handling frictions (Coase, 1937; Williamson, 1985; Jack et al., 2013; Nan & Peng, 2024). However, it remains empirically unexamined whether digital financial technology alters an informal firm's structural capacity to absorb utility overhead shocks. This leads to our central research question: *To what extent does digital payment adoption directly enhance labor productivity in informal micro-enterprises, and does it act as a working-capital liquidity buffer that mitigates the adverse productivity impacts of high electricity overhead costs in urban Cambodia?*

1.2 Research Objectives

To address these empirical and theoretical gaps, this study examines the nexus betweef digital mon adoptioney, electricity expenditures, and labor productivity among informal micro-enterprises in Cambodia. Grounded in intensive growth theory (Ahmed, 2006; Dollar & Sokoloff, 1990) and transaction cost economics (Flammer, 2018; Rindfleisch, 2020), this paper addresses two primary research questions:

(i) To evaluate the direct impact of physical ICT capital deepening (computer hardware access) and digital financial adoption (digital money usage) on labor productivity (sales per worker) in informal enterprises.
(ii) To examine whether digital money adoption moderates the effect of electricity cost per worker on labor productivity by serving as a working-capital liquidity buffer that alters the marginal return to energy intensity.

To resolve endogeneity and reverse causality, we analyze the 2024 World Bank Survey across four Cambodian cities using a 2SLS instrumental variable framework based on leave-one-out spatial cluster peer adoption rates. We contribute by integrating digital payments into the per-worker intensive growth framework, providing causal evidence on liquidity buffering, and identifying key policy priorities for informal digital inclusion.

The remainder of the manuscript is organized as follows: Section 2 reviews intensive growth theory, transaction cost economics, and empirical literature on enterprise digitalization to formulate testable hypotheses. Section 3 outlines the research context in Cambodia, describes the World Bank microdata, specifies the econometric production functions, and details the 2SLS identification strategy. Section 4 presents descriptive statistics, OLS regressions, 2SLS instrumental variable results, marginal crossover analyses, and econometric diagnostics. Finally, Section 5 synthesizes the empirical findings, outlines managerial and policy implications, and discusses limitations and future research avenues.

2. Literature Review and Hypothesis Development

2.1 Theoretical Framework

2.1.1 Intensive Growth Theory and the Micro-Production Function

We ground our empirical baseline in intensive growth theory (Ahmed, 2006; Solow, 1956). Sustainable labor productivity gains require capital deepening, ICT capital accumulation, and human capital augmentation rather than simple labor addition. For unbanked micro-enterprises, ICT intensity captures accessible technological capital (Atiyas & Dutz, 2021)and provides a framework for evaluating digital financial adoption.

2.1.2 Transaction Cost Economics and Liquidity Buffering

Transaction Cost Economics (TCE) offers a robust analytical framework for understanding how digital financial tools reduce structural operational frictions and protect enterprise working capital (Coase, 1937; Williamson, 1985; Rindfleisch, 2020). Coasean economic theory posits that firms incur substantial ex-ante transaction costs (such as search, negotiation, and contract formulation) alongside ex-post transaction costs (including monitoring, enforcement, and cash-reconciliation overhead). In emerging markets, informal enterprises operating with cash-based transaction systems face significant frictional losses. Cash handling entails non-trivial direct and indirect expenses, including time spent traveling to physical banking locations or cash points, heightened exposure to theft or loss, manual accounting discrepancies, and delayed payment settlements (Jack et al., 2013; Pankomera & van Greunen, 2019).

Digital payments and mobile money platforms directly reduce these ex-post transactional friction costs by enabling instant, verifiable, automated electronic settlements (Nan & Peng, 2024). By accelerating cash conversion cycles and reducing delays in customer receivables, digital financial technologies optimize working-capital liquidity (Williamson, 1985). In informal urban settings with high fixed utility costs, liquidity bottlenecks often force micro-entrepreneurs to cut production or reduce operating hours. Instant electronic payment mechanisms eliminate cash-flow delays, establishing a continuous liquidity buffer. This financial flexibility lets micro-enterprises absorb operational cash drains—such as high electricity overheads—without sacrificing productive capacity or facing stockout disruptions (Kabengele & Roessling, 2022; Nan & Peng, 2024).

2.1.3 Energy Consumption and Economic Growth: Macro and Micro Foundations

The relationship between energy consumption and economic performance is central to both macroeconomic growth models and microeconomic production theory. At the aggregate level, neoclassical growth models traditionally treated energy as an intermediate input, focusing primarily on capital, labor, and total factor productivity. However, modern ecological and resource-based economic frameworks emphasize that energy is a fundamental engine of production, directly determining the scale and velocity of economic activity (Boyd & Pang, 2000; Solow, 1956). Extensive macroeconomic literature identifies four primary causal hypotheses governing this relationship: the growth hypothesis (where energy directly drives growth), the conservation hypothesis (where economic expansion dictates energy demand), the feedback hypothesis (bidirectional causality), and the neutrality hypothesis (energy has negligible direct growth impact).

At the microeconomic enterprise level, energy—specifically electrical power—acts as a vital complementary input to physical capital and technological infrastructure (Ankrah et al., 2023; Kebede & Heshmati, 2020).

Reliable access to electricity enables micro-enterprises to adopt powered equipment, mechanize manual tasks, extend operating hours, and use digital payment and computing hardware. Consequently, energy expenditure per worker directly reflects how enterprises use capital and operate intensively. In informal micro-enterprises with severe capital constraints, energy expenditure is a major fixed utility overhead that can create cash-flow frictions. Understanding how energy inputs interact with financial liquidity and digital adoption is therefore crucial for explaining variations in labor productivity and operational resilience in informal economies.

2.2 Hypothesis Development

2.2.1 Physical ICT Capital and Labor Productivity

In informal firms, physical capital deepening mainly takes the form of ICT hardware such as computers and tablets. Computers enable structured record-keeping, inventory tracking, and managerial control (Aberra et al., 2022).

We propose:

Hypothesis 1 (H1): *Informal enterprises that adopt computer hardware achieve significantly higher sales per worker than non-adopting enterprises.*

2.2.2 Digital Financial Technology Adoption and Productivity Frictions

Mobile money and QR codes streamline commercial operations (World Bank, 2021). While digital payment adoption generally correlates with increased sales (Danquah & Owusu, 2021), micro-firms may experience initial adoption frictions or fixed transaction fees (Islam & Jolevski, 2019).

We test:

Hypothesis 2 (H2): *Informal enterprises that adopt digital money achieve higher sales per worker than non-adopters.*

2.2.3 The Interaction Between Electricity Costs and Digital Money: A Liquidity Buffering Perspective

As informal micro-enterprises scale up, extend operating hours, or deploy powered machinery, their electricity demand increases substantially (Ankrah et al., 2023). In informal economies, electricity is not merely a flexible operating expense but a mandatory fixed utility overhead that must be settled on strict payment schedules to avoid immediate disconnection. As energy expenditure per worker rises, cash-reliant micro-enterprises face acute cash-flow drains. Because informal firms typically operate with minimal working capital reserves and lack access to short-term credit facilities or formal overdrafts, large energy bills create working capital bottlenecks that restrict their ability to purchase raw materials, maintain inventory, or meet payroll (De Paula & Scheinkman, 2007; Kabengele & Roessling, 2022). Consequently, for cash-bound firms, rising energy intensity can yield diminishing or negative marginal returns to labor productivity because liquidity constraints disrupt operations.

Digital payments transform this operational dynamic by altering the firm's underlying liquidity mechanics. Standard commercial cash conversion cycles in cash-reliant informal sectors entail substantial frictional delays, including manual cash collection, physical trips to bank branches or agent points, reconciliation overhead, and exposure to theft or loss (Jack et al., 2013; Nan & Peng, 2024). Commercial digital payment platforms (such as QR-code-based mobile transfers and instant settlement networks like Cambodia's Bakong system) eliminate these friction points by providing real-time cash inflows directly into usable digital accounts. This constant velocity of money creates a continuous working-capital liquidity buffer, enabling entrepreneurs to settle high utility overheads seamlessly without locking up operational cash or depleting reserves earmarked for core production inputs (Williamson, 1985; Shaikh et al., 2023). By smoothing cash flow volatility and eliminating stockouts or operational halts caused by utility payment deadlines, digital payments allow energy-intensive micro-enterprises to fully leverage capital investments and achieve higher labor productivity.

Formally, we propose that digital payment adoption shifts the marginal return to electricity intensity from negative to positive:

Hypothesis 3 (H3): *Digital money adoption positively moderates the relationship between electricity expenditure per worker and labor productivity, such that the net marginal return to electricity intensity is higher for digital money adopters than for cash-reliant enterprises.*

3. Methodology

3.1 Data

This study employs microdata from the World Bank's 2024 Cambodia Informal Sector Enterprise Survey (CSIS). The dataset provides comprehensive firm-level observations collected across four major urban economic hubs in Cambodia: Phnom Penh, Battambang, Siem Reap, and Sihanoukville. The survey targets informal micro and small enterprises (MSEs)—non-agricultural, privately owned commercial entities that operate without formal business registration with national or municipal authorities. To build a representative sample frame of

unregistered firms without official administrative registers, the World Bank used a multi-stage spatial block-enumeration sampling methodology. Within each target city, geographic areas were divided into enumeration blocks (sampling clusters, identified by id_cluster), followed by a comprehensive door-to-door physical census of non-residential and home-based enterprise establishments.

Although the full survey surveyed 1,759 informal enterprises in Cambodia, our regression analysis is limited to a smaller sample size due to missing key financial variables. Many informal enterprises do not pay formal employee wages, leading to zero or unreported labor costs. The sample size, therefore, decreases to N = 347 for the OLS models and N = 273 for the 2SLS specifications across 52 spatial clusters.

3.2 Empirical Model

Grounding our formulation in intensive growth theory (Ahmed, 2006; Dollar & Sokoloff, 1990), we specify an aggregate Cobb–Douglas production function for firm i in sector s:

$$Y_i = A_i K_i^{\alpha} (ICT_i)^{\lambda} (HC_i)^{\theta} L_i^{1-\alpha-\lambda-\theta}$$

Assuming constant returns to scale across production factors and dividing both sides by total labor input L_i yields:

$$\frac{Y_i}{L_i} = A_i \left(\frac{K_i}{L_i}\right)^{\alpha} \left(\frac{ICT_i}{L_i}\right)^{\lambda} \left(\frac{HC_i}{L_i}\right)^{\theta}$$

Taking natural logarithms produces the linear per-worker intensive growth specification:

$$\ln\left(\frac{Y_i}{L_i}\right) = \ln A_i + \alpha \ln\left(\frac{K_i}{L_i}\right) + \lambda \ln\left(\frac{ICT_i}{L_i}\right) + \theta \ln\left(\frac{HC_i}{L_i}\right) + \epsilon_i$$

Because informal enterprise surveys lack detailed balance-sheet measures of fixed machinery, we proxy physical ICT capital intensity (*K/L)* with the binary indicator for computer hardware usage (dcomputer_i). Digital technology intensity (*ICT/L*) is represented by digital money adoption (ddigmoney_i). We measure human capital intensity (*HC/L*) using log human capital costs per worker (lCostperL_i), which includes wages, training, and employee welfare in Cambodian Riels. To test the energy interaction hypothesis, we also introduce log electricity expenditure per worker (lEperL_i) and its multiplicative interaction with digital money.

The empirical estimating equations are specified as follows:

Model 1 (Baseline Additive Model):

$$ln(SalesperL_i) = \beta_0 + \beta_1(dcomputer_i) + \beta_2(ddigmoney_i) + \beta_3 ln(EperL_i) + \beta_4(computerskill_i) + \beta_5 ln(CostperL_i) + \epsilon_i \quad (1)$$

Model 2 (Moderated Interaction Model):

$$ln(SalesperL_i) = \gamma_0 + \gamma_1(dcomputer_i) + \gamma_2(ddigmoney_i) + \gamma_3 ln(EperL_i) + \beta_4\big(ddigmoney_i * ln(EperL_i)\big) + \beta_5(computerskill_i) + \beta_6 ln(CostperL_i) + u_i \quad (2)$$

Where:

(i). $\ln(SalesperL_i)$ is log monthly sales revenue per full-time worker.

(ii). $dcomputer_i$ is a dummy variable equal to 1 if the business utilizes computers or tablets, and 0 otherwise.

(iii). $ddigmoney_i$ is a dummy variable equal to 1 if the business utilizes digital payment platforms/mobile money, and 0 otherwise.

(iv). $\ln(EperL_i)$is log monthly electricity cost per worker.

(v). $computerskill_i$ is the proportion of workers possessing functional computer skills.

(vi). $\ln(CostperL_i)$ is log human capital expenditure per worker.

(vii). ϵ_i and u_i are disturbance terms.

3.3 Identification Strategy

Reverse causality and unobserved managerial traits pose endogeneity risks. We implement a 2SLS strategy using the leave-one-out spatial cluster peer adoption rate $Z_{i,c}$ as an instrument for digital payment adoption (Atiyas & Dutz, 2021; Nan & Peng, 2024):

To establish identification and purge reverse causality, we implement a Two-Stage Least Squares (2SLS) instrumental variable strategy. Drawing on empirical identification strategies in informal enterprise literature (e.g., Atiyas & Dutz, ; Danquah & Owusu, 2021; Nan & Peng,), we exploit the spatial sampling structure of the survey and instrument an individual firm's digital payment adoption using the leave-one-out cluster peer adoption rate $Z_{i,c}$ across the 359 geographic sampling clusters (id_cluster):

$$Z_{i,c} = \frac{1}{N_c - 1} \sum_{j \neq i}^{N_c} \text{ddigmoney}_{j,c}$$

where N_c is the total count of sampled informal enterprises within spatial sampling cluster c, and $\text{ddigmoney}_{j,c}$ indicates the binary adoption status of neighboring peer enterprise j.

Adoption of digital financial tools is driven by strong local network externalities, peer demonstration effects, and shared payment literacy. When neighboring vendors and local market suppliers predominantly transact digitally, entrepreneurs face strong customer expectations and lower adoption frictions ($F > 10$ in first-stage diagnostics).

Instrumenting the Interaction Term:

To instrument the interaction term ($\text{ddigmoney}_i \times \ln(\text{EperL}_i)$), we use ($Z_{i,c} \times \ln^*\text{EperL}_i$) as the second excluded instrument (Wooldridge, 2010), clustering standard errors at the sampling-cluster level.

Standard errors across all stages are clustered at the sampling-cluster level (id_cluster; 52 clusters in the estimation sample) to account for spatial intra-cluster correlation.

4. Empirical Results

4.1 Descriptive Statistics

Computer hardware usage is limited (8.96%), and worker digital skills average 17.46%. In contrast, digital payment adoption stands at 55.77%. Electricity cost per worker varies substantially across firms.

Table 1: Descriptive Statistics

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
lSalesperL	Log sales per worker	1,276	11.531	3.253	2.996	16.524
dcomputer	Dummy for computer/tablet use	1,752	0.090	0.286	0.000	1.000
ddigmoney	Dummy for digital money adoption	1,759	0.558	0.497	0.000	1.000
lEperL	Log electricity cost per worker	747	7.863	3.426	1.609	14.509
computerskill	Proportion of workers with computer skills	921	0.175	0.345	0.000	1.000
lCostperL	Log human capital cost per worker	981	9.873	3.095	4.605	16.524

Notes: Summary statistics are based on firm-level microdata from the 2024 World Bank Cambodia Informal Sector Enterprise Survey across Phnom Penh, Battambang, Siem Reap, and Sihanoukville. All financial figures are measured in Cambodian Riels (KHR).

Computer adoption is highest in Sihanoukville (29%), whereas digital payments are most prevalent in Siem Reap (71%) and Phnom Penh (58%). Services (59%) and retail (55%) lead in payment adoption. Informal service-oriented businesses report the highest rate of digital money adoption (59%), followed by retail goods reselling (55%) and small manufacturing enterprises (48%).

4.2 Regression Results

Table 2 presents the Ordinary Least Squares (OLS) regression estimates. Model 1 reports the baseline additive model, while Model 2 incorporates the interaction between digital money adoption and log electricity expenditure per worker.

Table 2: OLS Regression Results (Dependent Variable: ln(Salesperl)

Explanatory Variables	Model 1 (Baseline)	Model 2 (Interaction)
Computer Use (dcomputer)	2.699***	2.116***
	(0.336)	(0.328)
Digital Money Adoption (ddigmoney)	-1.978***	-5.693***
	(0.251)	(0.595)
Log Electricity Costs per Worker (lEperL)	0.009	-0.149**
	(0.075)	(0.075)
Digital Money × Log Electricity Costs	—	0.491***
	—	(0.072)
Computer Skills Share (computerskill)	0.327	0.472
	(0.386)	(0.363)
Log Human Capital Costs per Worker (lCostperL)	0.545***	0.434***
	(0.076)	(0.073)
Constant	6.264***	8.625***
	(0.424)	(0.529)
Observations	347	347
R-squared	0.569	0.621
Adjusted R-squared	0.563	0.614
F-statistic	90.11***	92.73***
Residual Degrees of Freedom	341	340

Notes: Standard errors are reported in parentheses directly below coefficient estimates. Models are estimated using Ordinary Least Squares (OLS) on firm-level microdata from the 2024 World Bank Cambodia Informal Sector Enterprise Survey. The dependent variable is log monthly sales revenue per full-time worker (ln(SalesperL)). *** p < 0.01, ** p < 0.05, * p < 0.10.

4.1 Regression Results

Physical ICT Capital (H1 Supported): Computer hardware usage (dcomputer) exerts a large, statistically significant positive effect on sales per worker across both specifications ($\beta = 2.116, p < 0.001$ in Model 2). Controlling for human capital and energy costs, firms utilizing computers achieve substantially higher productivity, underscoring the vital role of basic ICT infrastructure in operational planning and inventory control.

Direct Effect of Digital Money (H2 Evaluated): In Model 1, the unconditional coefficient on ddigmoney is negative ($\beta = -1.978, p < 0.001$). In Model 2, the baseline coefficient ($\gamma_2 = -5.693, p < 0.001$) reflects the conditional shift at ln(EperL=0 . This suggests that for micro-enterprises operating at minimal scale and with low overhead, adopting digital payments does not automatically translate into immediate labor productivity gains, likely due to transaction fees, onboarding friction, and subsistence operating scales.

The Moderating Interaction (H3 Supported): The interaction term ddigmoney × lEperL is positive and highly significant ($\gamma_4 = 0.491, p < 0.001$). Including this interaction term increases the explained variance from R^2 = 0.5692 to R^2 = 0.6207 ($\Delta R^2 = 0.0515, F = 46.10, p < 0.001$), demonstrating that the moderation effect is economically and statistically meaningful.

Marginal Effects and Crossover Analysis:
In Model 2, the marginal effect of electricity costs on productivity depends on payment adoption. For firms utilizing digital money, electricity consumption is strongly and positively associated with sales per worker. The crossover point occurs at $\ln(EperL) \approx 11.59$. Below this threshold, non-adopters have higher predicted sales per worker; above it, digital payment adopters gain a distinct productivity advantage by buffering working-capital liquidity. Because this crossover threshold represents a relatively high energy intensity level, net positive productivity gains from digital payments accrue primarily to the upper decile of energy-intensive firms (such as larger workshops or refrigerated retail outlets), whereas small subsistence vendors face net baseline adoption frictions.

Figure 1: Margins plot

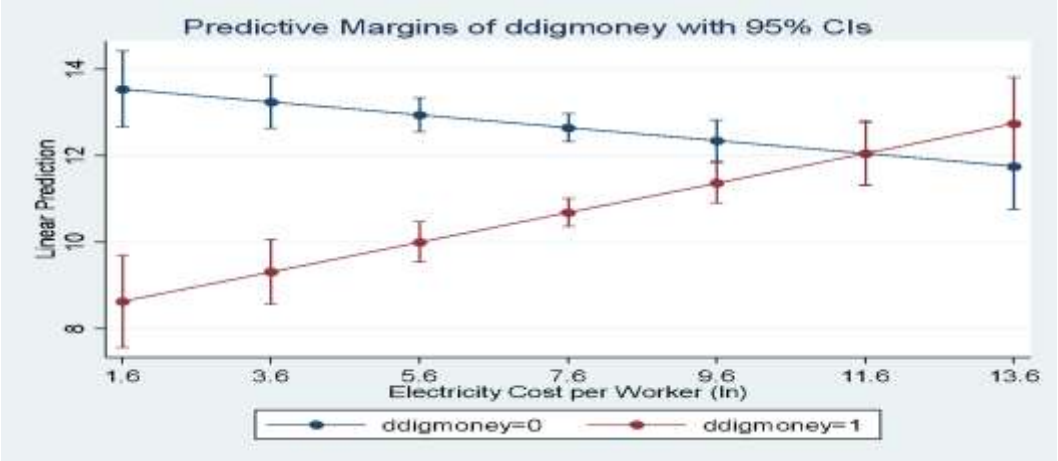


Figure 1 shows that a higher electricity cost per worker is associated with higher linear predicted sales per worker in the group using digital money (ddigmoney=1). The group with ddigmoney=1 consistently has higher predicted sales per worker than does the group with ddigmoney=0.

4.2 Robustness Analysis
Table 3 presents the 2SLS estimates, first-stage diagnostics, and endogeneity tests.

Table 3: Instrumental Variable (2SLS) Estimation and Endogeneity Tests
(Dependent Variable: ln(SalesperL) , Standard errors clustered by id_cluster)

Second-Stage Regressors	**2SLS Coeff.**	**Std. Err.**	**z-stat**	**p-value**
Digital Money Adoption (ddigmoney)	-10.376***	(2.661)	-3.90	0.000
Digital Money × Log Electricity Costs	0.848***	(0.294)	2.88	0.004
Computer Use (dcomputer)	1.573**	(0.706)	2.23	0.026
Computer Skills Share (computerskill)	0.485	(0.549)	0.88	0.377
Log Human Capital Costs per Worker (lCostperL)	0.415**	(0.176)	2.36	0.018
Log Electricity Costs per Worker (lEperL)	-0.298	(0.188)	-1.59	0.113
Constant	11.155***	(1.736)	6.43	0.000
Model Diagnostics & Identification Tests				
Observations (N)	273			
Clusters (id_cluster)	52			
Centered R-squared / Root MSE	0.536 / 2.308			
First-Stage F: Digital Money	11.890			0.000

Second-Stage Regressors	2SLS Coeff.	Std. Err.	z-stat	p-value
Sanderson–Windmeijer F: Digital Money	19.310			0.000
First-Stage F: Digital Money × Electricity Costs	10.610			0.000
Sanderson–Windmeijer F: Digital Money × Electricity Costs	17.720			0.000
Kleibergen–Paap rk LM Stat (Underidentification)	8.691			0.003
Cragg–Donald Wald F Statistic	14.546			
Kleibergen–Paap rk Wald F Statistic	7.443			
Stock–Yogo Critical Value (10% Maximal IV Size)	7.030			
Anderson–Rubin Wald Test (Weak-Instrument Robust)	15.620			0.000
Endogeneity Test (Durbin–Wu–Hausman F-stat)	4.499			0.016
Overidentification Test (Hansen J-stat)	0.000			—

Notes: Standard errors adjusted for clustering at the sampling cluster level (id_cluster; 52 clusters) are reported in parentheses below coefficient estimates. Models are estimated using Two-Stage Least Squares (2SLS) on firm-level microdata from the 2024 World Bank Cambodia Informal Sector Enterprise Survey. The dependent variable is log monthly sales revenue per full-time worker (ln(SalesperL)). Excluded instruments are the cluster peer digital payment adoption rate and its interaction with log electricity costs per worker. The overidentification test reports zero degrees of freedom as the model is exactly identified. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Interpretation and Empirical Inferences from the 2SLS Model:

(i) Reverse Causality: The Durbin–Wu–Hausman test strongly rejects the null hypothesis that digital money adoption and its interaction are exogenous ($F(2,51) = 4.499$, $p = 0.0159$; $\chi^2(2) = 5.201$, $p = 0.0742$. This confirms endogeneity in OLS, validating the need for the 2SLS framework.

(ii) Instrument Strength and Identification: Both first-stage equations show strong explanatory power: the excluded instruments yield F-statistics of 11.89 ($p < 0.001$)() for ddigmoney and 10.61 ($p < 0.001$)() for the interaction term, exceeding the conventional threshold of 10. The Sanderson–Windmeijer multivariate conditional F-tests are 19.31 and 17.72 ($p < 0.001$), confirming separate identification. The Kleibergen–Paap rk LM test rejects underidentification $\chi^2(2) = 8.691$, $p = 0.0032$, and the Wald *F*-statistic exceeds the Stock–Yogo 10% maximal IV critical value (7.03), ruling out weak instruments. Weak-instrument-robust Anderson–Rubin tests reject the null of zero joint coefficients $\chi^2(2) = 15.62$, $p = 0.0004$.

The instrumental variable (2SLS) analysis confirm endogeneity and reverse causality in OLS estimates. By instrumenting digital payment adoption using spatial cluster peer adoption rates, we isolate the true causal effect of digital financial tools.

(iii) Causal Impact of Digital Money and Moderation: Purged of reverse causality, the moderating interaction term (ddig_x_lEperL) remains positive and statistically significant ($\gamma_4 = +0.848$, $z = 2.88$, $p = 0.004$). The 2SLS interaction coefficient is larger than the OLS coefficient (0.848 vs. 0.491), indicating that unobserved constraints in OLS caused downward attenuation bias. For digital money adopters, the marginal return to electricity intensity is positive and strong.

This confirms that digital money serves as a vital liquidity and transaction-smoothing buffer, especially as operations expand into higher electricity costs and larger scales. The estimated crossover threshold of $\ln(\text{EperL})^* \approx 12.24$ indicates that positive productivity gains from digital payment adoption take place among the top tier of energy-intensive informal enterprises.

5. Conclusion

5.1 Main Conclusion

Physical ICT hardware access (computers and tablets) results in significant positive labor productivity gains, confirming that hardware capital deepening provides operational ability for firm performance. Digital money adoption strongly and positively moderates electricity cost intensity. It implies that for digital payment adopters, higher energy intensity translates into increased sales per worker. Digital payments play the role of working-capital buffer, enabling informal firms to expand productiong, entaileds by more energy use, without cash constraints.

5.2 Managerial and Practical Implications

Owner-managers of informal enterprises should optimize by integrating digital payment platforms, which enables instant reinvestment in production inputs, raw materials, and inventory. Managers must also align these technological investments with their operational scale, pairing energy-intensive expansion - such as powered machinery - with digital payment mechanisms to benefit from liquidity buffering beyond the critical energy threshold. To fully realize these advantages, micro-enterprises should prioritize basic hardware deepening and administrative digital skills by acquiring accessible computational tools, such as tablets or computers, to move beyond manual logging and achieve structured record-keeping, precise stock replenishment, and effective working capital management.

5.3 Policy Recommendations

To unlock the full productive potential of informal micro-enterprises, public policymakers and financial institutions must implement targeted interventions that address both structural hardware deficits and grid infrastructure constraints. Given the low national adoption of computer hardware in informal businesses, international development partners and local authorities should subsidize informal enterprises with ICT equipment, such as computers, tablets and POS terminals to improve their operational capacity and labor productivity. In addition, financial institutions should maintain zero-commission fee structures, removing financial bottlenecks and encouraging digital adoption among low-margin small enterprises.

5.4 Limitations and Directions for Future Research

Several limitations of this study offer directions for future research. First, deletion due to sample attrition restricts our analysis to a smaller sample size of informal enterprises with complete utility and wage data. Although our 2SLS instrumental variable design rigorously addresses endogeneity and reverse causality, the empirical analysis relies on cross-sectional microdata from the 2024 survey; future studies should employ longitudinal panel dataset structures to track micro-enterprise productivity over time and observe post-adoption dynamic adjustments across business cycles. Finally, while our sample spans four major Cambodian urban centers, expanding the geographic and sectoral scope to include rural informal economies and cross-country comparisons across Southeast Asia would improve generalizability.

Acknowledgements

This research is funded by Vietnam National University HoChiMinh City (VNU-HCM) under a project within the framework of the Program titled “Strengthening the capacity for education and basic scientific research integrated with strategic technologies at VNU-HCM, aiming to achieve advanced standards comparable to regional and global levels during the 2025-2030 period, with a vision toward 2045.

Funding

This research is funded by Vietnam National University HoChiMinh City (VNU-HCM).

Author Contributions

Tung Nguyen: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Writing – Original Draft, Writing – Review & Editing.

Data Availability Statement

The datasets analyzed during the current study are available from the World Bank's Microdata Library upon request.

Conflicts of Interest

The author declares no conflicts of interest.

Ethics Statement

Not applicable, as this study uses secondary anonymized survey data provided by the World Bank.

References

[1] Aberra, A., Aga, G., Jolevski, F., & Karalashvili, N. (2022). *Understanding Informality: Comprehensive Business-Level Data and Descriptive Findings*. World Bank Policy Research Working Paper No. 9959. World Bank, Washington, DC.
[2] Ahmed, E. M. (2006). ICT and human capital role in achieving knowledge-based economy: Applications on Malaysia's manufacturing. *Journal of Information & Knowledge Management*, 5(2), 117–128.
[3] Ankrah, I., Appiah-Kubi, M., Twumasi-Ankrah, S., Sackey, F. G., Asravor, R., Boahemaa, B., Donkor, D., Arthur, L., Lamptey, C., & Mochiah, E. (2023). Modeling ICT development and electricity consumption in emerging digital economies. *Energy Policy*, 182, 113745.
[4] Atiyas, İ., & Dutz, M. A. (2021). *Digital Technology Uses among Informal Micro-Sized Firms: Productivity and Jobs Outcomes in Senegal*. World Bank Policy Research Working Paper No. 9632. World Bank, Washington, DC.
[5] Boyd, G. A., & Pang, J. X. (2000). Estimating the linkage between energy efficiency and productivity. *Energy Policy*, 28(5), 289–296.
[6] Danquah, M., & Owusu, S. (2021). *Digital Technology and Productivity of Informal Enterprises: Empirical Evidence from Nigeria*. UNU-WIDER Working Paper No. 2021/54. United Nations University.
[7] De Paula, Á., & Scheinkman, J. A. (2007). *The Informal Sector*. NBER Working Paper No. 13486. National Bureau of Economic Research, Cambridge, MA.
[8] Dollar, D., & Sokoloff, K. (1990). Patterns of productivity growth in South Korean manufacturing industries, 1963–1979. *Journal of Development Economics*, 33(2), 309–327.
[9] ILO. (2023). *Workers in the Cambodian Informal Economy*. International Labour Organization Country Office, Geneva.
[10] Islam, A., & Jolevski, F. (2019). *The Digital Disconnect of Informal Businesses*. World Bank Group Enterprise Note Series No. 41. World Bank, Washington, DC.
[11] Jack, W., Ray, A., & Suri, T. (2013). Transaction networks: Evidence from mobile money in Kenya. *American Economic Review*, 103(3), 356–361.
[12] Kabengele, C., & Roessling, U. (2022). Mobile money use and firm productivity in Africa: A comparison of formal and informal firms. *African Development Review*, 34(3), 358–372.
[13] Kebede, S. G., & Heshmati, A. (2020). Energy use and labor productivity in Ethiopia: The case of the manufacturing industry. *Energies*, 13(11), 2714.
[14] La Porta, R., & Shleifer, A. (2014). Informality and development. *Journal of Economic Perspectives*, 28(3), 109–126.
[15] Nan, W. V., & Peng, Y. (2024). Mobile money, stockouts and informal microenterprise performance: Evidence from sub-Saharan Africa. *Journal of Development Studies*, 60(4), 589–608.
[16] Pankomera, R., & van Greunen, D. (2019). Opportunities, barriers, and adoption factors of mobile commerce for the informal sector in developing countries in Africa: A systematic review. *Electronic Journal of Information Systems in Developing Countries*, 85(5), e12096.
[17] Rindfleisch, A. (2020). Transaction cost analysis: Past, present, and future. *AMS Review*, 10(1), 85–97.
[18] Savuth, C., & Oum, S. (2023). Digital transformation in Cambodia: Policies, strategies, supporting factors and infrastructure. *Southeast Asian Economies*, 40(1), 145–172.
[19] Shaikh, A. A., Glavee-Geo, R., Karjaluoto, H., & Hinson, R. E. (2023). Mobile money as a driver of digital financial inclusion. *Technological Forecasting and Social Change*, 186, 122158.
[20] Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70(1), 65–94.
[21] Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.). MIT Press, Cambridge, MA.
[22] World Bank. (2021). *Data from the Global Findex 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19*. World Bank, Washington, DC.