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Digital Intensity, Global Value Chains, and Resilience: Evidence on the MSME digital divide in Southeast Asia[1]

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Abstract

This paper examines the determinants and consequences of digitalization among micro, small, and medium-sized enterprises (MSMEs) in Southeast Asia. Using firm-level survey data from Indonesia, Malaysia, and Viet Nam covering 23 digital tools, we distinguish between digital adoption breadth (extensive margin) and depth (intensive margin). Drawing on technology diffusion theory, both margins are positively associated with managerial human capital and global value chain participation, while external support is more strongly associated with adoption depth. During COVID-19, firms with higher digitalization were more likely to maintain pre-crisis sales, with stronger associations for depth than breadth. These findings suggest that economic benefits depend less on the range of tools adopted than on their effective integration into operations. Policies targeting the MSME digital divide may therefore be more effective when focused on strengthening digital use capabilities rather than expanding adoption alone.

Keywords: MSMEs; Digitalization; Digital divide; Global value chains; Firm resilience; Southeast Asia

JEL classification: O33, D22, O12

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1 Introduction

Reducing the digital divide among micro, small, and medium-sized enterprises (MSMEs) has become a central policy priority in developing economies. Digital technologies can lower transaction costs, expand market access, and improve operational efficiency, thereby contributing to productivity growth and economic development (Fernández-Portillo et al., 2020; Appiah-Otoo & Song, 2021). However, adoption remains highly uneven across firms. MSMEs typically lag behind larger firms in adopting information and communication technologies (ICTs) (Kuwayama, Tsuji, & Ueki, 2005). These disparities may reflect not only differences in access to technology but also differences in managerial capacity, organizational readiness, and integration into business networks (Paunov & Rollo, 2016; Gnangnon, 2019). Understanding why some MSMEs adopt digital technologies more intensively than others has therefore become an important research and policy question.

The COVID-19 pandemic highlighted the economic relevance of this digital divide. Lockdowns and mobility restrictions disrupted face-to-face transactions, supply chains, and labor mobility, increasing reliance on digital tools for maintaining operations. Firms used online sales channels, digital payments, and remote coordination technologies to adapt to these constraints. A growing literature documents accelerated digital adoption during the pandemic (Gao et al., 2023; Modi, 2022; Redjeki and Affandi, 2021, Avalos et al., 2024). At the same time, the crisis raised concerns about widening disparities in firm survival, as more digitally capable firms were better positioned to withstand disruptions (Khalil, Abdelli, and Mogaji, 2022). These developments point to two closely related empirical questions: what determines digitalization among MSMEs, and whether digitalization enhances firm resilience during large shocks.

Despite their importance, existing empirical studies face two key limitations. First, many studies measure digitalization using a narrow set of indicators—such as internet use or participation in e-commerce (e.g., Paunov and Rollo, 2016; Oikawa et al., 2025a, 2025b). While informative, such measures capture only specific aspects of digital engagement and do not reflect the broader integration of digital technologies across business functions. Second, existing studies rarely distinguish between the adoption of digital tools and their effective use. As a result, the literature provides limited evidence on whether the economic benefits of digitalization depend primarily on the breadth of technologies adopted or on how intensively they are used within firms.

These gaps are particularly relevant in Southeast Asia, where MSME digitalization has become a central component of inclusive growth strategies. Governments and development institutions in the region have introduced a range of initiatives aimed at promoting digital onboarding, managerial upgrading, and participation in online marketplaces (Oikawa et al., 2024). However, the effectiveness of such policies depends on understanding both the determinants of digitalization and the channels through which digital technologies affect firm performance.

To address these issues, this paper uses a unique firm-level survey dataset covering MSMEs in Indonesia, Malaysia, and Viet Nam. The survey records the adoption of 23 digital tools spanning multiple business functions, including foundational communication and computing tools, procurement and logistics technologies, sales and marketing platforms, operational infrastructure, and advanced production technologies. Using these data, we construct two complementary measures of digital adoption: (1) digital adoption breadth, capturing the range of digital technologies adopted within firms, and (2) digital adoption depth, capturing the intensive margin of digitalization through the share of workers engaged in digital-related tasks. This distinction allows us to differentiate between the extensive and intensive margins of digital adoption and to examine how these dimensions are associated with firm performance.

The paper investigates two related questions. First, we examine the determinants of digitalization among MSMEs. Drawing on the technology diffusion literature (e.g., Stoneman and Battisti, 2010), we test whether digital adoption is associated with managerial human capital, participation in global value chains (GVCs), exposure to public and private support programs, and the surrounding peer environment. Second, we examine whether digitalization is associated with firm resilience during the COVID-19 shock, measured by the ability to maintain sales relative to the pre-pandemic period.

Our empirical framework is guided by diffusion models summarized by Stoneman and Battisti (2010), which emphasize firm heterogeneity (rank effects), information spillovers, and competitive interactions (stock effects). These mechanisms provide a useful framework for interpreting both adoption patterns and performance outcomes, particularly in environments where digital technologies are diffusing rapidly across firms.

This paper contributes to the literature in three main ways. First, it provides comprehensive firm-level evidence on digitalization among MSMEs in developing economies by measuring digital adoption across a broad range of technologies and business functions rather than focusing on a single digital tool. Second, it distinguishes between the extensive and intensive margins of digital adoption, showing that while digital adoption breadth is associated with firm characteristics and external linkages, digital adoption depth is more strongly and consistently associated with firm resilience. Third, it extends the emerging literature on digitalization and resilience (e.g., Li et al., 2023; Oikawa et al., 2025a, 2025b), which primarily focuses on specific technologies such as e-commerce and digital platforms, by examining multiple business functions and dimensions of digital adoption.

The findings have important policy implications. Bridging the digital divide among MSMEs requires more than expanding access to digital technologies. Effective digital transformation depends on managerial capability, organizational adaptation, and integration into global business networks. Moreover, as digital adoption becomes more widespread, its role shifts from a source of firm performance advantage to a baseline requirement for participation in modern markets. Policies that strengthen managerial capabilities and facilitate participation in value chains and digital platforms are therefore central to inclusive digital transformation.

The remainder of the paper is structured as follows. Section 2 describes the literature review and hypotheses. Section 3 describes the data. Section 4 outlines the empirical strategy. Section 5 reports the summary statistics. Section 6 provides the results. Section 7 discusses policy implications. Section 8 concludes.

2 Literature Review and Hypotheses

This section develops the empirical framework and testable hypotheses by integrating insights from the technology diffusion literature and recent evidence on digitalization and firm performance. We distinguish between (i) the determinants of digital adoption and (ii) its implications for firm resilience during the COVID-19 shock. Additional details on the conceptual framework are provided in Appendix A.

2.1 Determinants of digital adoption

A central insight from the technology diffusion literature is that firms differ in their incentives and ability to adopt new technologies. In the rank model of diffusion, firms adopt technologies when their expected net benefits exceed adoption costs, implying that heterogeneity in capabilities and environments leads to variation in adoption outcomes (Stoneman and Battisti, 2010). A large empirical literature shows that digital adoption depends not only on technology availability but also on complementary organizational and managerial capabilities. Implementing digital technologies requires changes in workflows, coordination, and learning processes, making adoption contingent on firm-level capabilities (Bresnahan et al., 2002; Bloom et al., 2012). Recent qualitative research further highlights that value creation from digital technologies depends on how digital resources are combined with organizational knowledge, routines, and human capabilities within firms and across business relationships (Ferreira et al., 2025). Qualitative evidence from SMEs further emphasizes the importance of managerial readiness, digital skills, and organizational culture in shaping successful digitalization processes (Kallmuenzer et al., 2025).

Firm characteristics such as size, age, and owner human capital serve as proxies for these capabilities. Larger firms typically possess greater financial and technical resources, enabling them to adopt more complex technologies (Geroski, 2000). Firm age captures accumulated experience but may also reflect organizational rigidity, leading to ambiguous empirical effects (Stoneman and Battisti, 2010). In MSMEs, owner characteristics play a central role in shaping adoption decisions. More educated managers are better able to evaluate uncertain technologies and manage implementation processes (Bartel and Lichtenberg, 1987), a pattern consistent with evidence of substantial heterogeneity in management practices across small firms in developing counties (McKenzie and Woodruff, 2017). In contrast, gender differences are less systematic once firm-level characteristics are controlled for (Croson and Gneezy, 2009; Aterido et al., 2013).

Existing evidence indicates that digital adoption depends on complementary organizational and managerial capabilities, but most of this evidence comes from large firms in advanced economies. Whether similar patterns hold for MSMEs in developing countries remains an open question. In particular, while education is generally associated with technology adoption, it is unclear which levels of owner human capital are most relevant in small firms, where managerial roles are highly concentrated. This motivates an empirical assessment of how firm characteristics and managerial attributes are associated with digital adoption in this context.

H1 Firm capability hypothesis*: firms with stronger organizational and managerial capacity exhibit higher digital adoption.*

Beyond internal capabilities, participation in GVCs can increase the expected returns to digital adoption. Firms integrated into GVCs are often required to comply with standards related to quality control, traceability, and coordination, many of which rely on digital technologies (Gereffi et al., 2005). These requirements raise the benefits of adopting digital tools for communication, inventory management, and data exchange. Empirical evidence shows that internationally connected firms tend to adopt more advanced technologies and achieve higher productivity (Bernard and Jensen, 1999; Helpman et al., 2004; De Loecker, 2007). These patterns reflect both self-selection of more capable firms into global markets and learning effects arising from international engagement, including direct capability building through exposure to global buyer requirements (Atkin, Khandelwal, and Osman, 2017). Interactions with multinational firms (MNFs) may also generate knowledge spillovers that facilitate technology adoption (Javorcik, 2004). Using firm-level data from developing countries, Delera et al. (2022) show that firms integrated into GVCs are more likely to adopt Industry 4.0 technologies.

Within the rank model that emphasizes heterogeneity in capabilities and environments in technology diffusion, the connectivity with MNFs differentiates the adoption of digital technologies between firms. These mechanisms suggest that internationally connected firms face higher expected returns to digitalization. While this relationship is well established in studies of exporters and large firms, there is more limited evidence on how multinational linkages shape digital adoption among MSMEs in developing countries. In particular, it remains unclear whether linkages to MNFs operate primarily through demand-side requirements, supply-chain integration, or knowledge spillovers in this context. This motivates an empirical examination of the association between multinational linkages and digital adoption in MSMEs.

H2 Network integration hypothesis*: firms participating in GVCs exhibit higher digital adoption.*

External support and capability-building programs may also influence firms' adoption of digital technologies. Training, consulting, and advisory interventions can improve managerial practices, reduce informational barriers, and strengthen firms' ability to implement new technologies. Experimental evidence shows that management consulting can substantially improve firm performance (Bloom et al., 2013), while reviews of business training programs document improvements in managerial practices among small firms, albeit with heterogeneous impacts on firm outcomes (McKenzie and Woodruff, 2014; McKenzie, 2021). Related management research also suggests that external support can complement firms' innovation and adaptation efforts during periods of organizational change (Adam and Alarifi, 2021).

However, it remains unclear whether such support translates into greater digital adoption among MSMEs in developing countries. While support programs are often designed to promote digitalization, their effectiveness in encouraging firms to adopt digital technologies is still an open empirical question, particularly in contexts where firms face resistance to organizational change or constraints in financial resources, digital skills, and implementation capacity (Kallmuenzer et al., 2025). This motivates an empirical examination of the association between exposure to public and private support and digital adoption among MSMEs.

H3 External support hypothesis*: firms exposed to public or private support ecosystems exhibit higher digital adoption.*

2.2 Digital adoption and firm resilience

While technology diffusion models explain the determinants of adoption, the economic consequences of digital adoption depend on how digital technologies affect firm performance. Firm-level evidence shows that IT investment generates sustained productivity gains as firms learn to integrate digital systems into their operations (Brynjolfsson and Hitt, 2000, 2003). The importance of digital tools became particularly salient during the COVID-19 pandemic, when restrictions on physical interaction increased reliance on digital solutions. Cross-country evidence from the World Bank Business Pulse Surveys documents a sharp rise in the use of digital technologies during this period (Apedo-Amah et al., 2020), suggesting that such tools served as an important mechanism for adjustment.

The existing literature primarily examines specific types of digital technologies. Operational tools—such as inventory management systems, EDI, and real-time logistics platforms—are associated with improvements in supply chain coordination. Rai et al. (2006) show that digitally enabled integration enhances information visibility and responsiveness by reducing distortions such as the bullwhip effect. In the context of COVID-19, firms with such capabilities may have been better able to adjust procurement, inventory, and delivery decisions in response to disruptions.

Market-interface tools (e.g., e-commerce platforms, digital marketing, and online marketplaces) facilitate demand-side adaptation by enabling alternative sales channels. Evidence from Chinese listed retailers suggests that participation in third-party e-commerce platforms enhanced resilience during the pandemic (Li et al., 2023). Similarly, evidence from Southeast Asian MSMEs indicates that online sales tools did not immediately offset early lockdown losses but became increasingly beneficial as firms adapted over time (Oikawa et al., 2025a, 2025b). Broader evidence links digital organizational capacity to COVID-19 resilience across firm types and contexts (Bai et al., 2021; Calza et al., 2023).

Despite these insights, less is known about how the overall extent of digitalization within firms is associated with performance during large and prolonged shocks, particularly for MSMEs in developing countries. The COVID-19 shock was characterized by persistent and evolving disruptions—such as lockdown-induced supply constraints and demand contractions transmitted through income and sectoral linkages (Guerrieri et al., 2022)—which makes the relationship between digitalization and firm performance non-trivial. While digital technologies operate through different functional channels, existing evidence provides limited guidance on whether broader digital adoption—capturing the combined adoption of multiple tools—is systematically associated with resilience. Accordingly, this relationship remains an empirical question.

H4 Resilience hypothesis*: Greater digital adoption is associated with stronger firm resilience during the COVID-19 pandemic.*

3 Data

3.1 Dataset

This study uses unique firm-level survey data on digital technology adoption among MSMEs in Indonesia, Malaysia, and Viet Nam. The survey was conducted in 2023 by the Economic Research Institute for ASEAN and East Asia (ERIA) and collects retrospective information on firm characteristics, digital tool adoption, business relationships, exposure to support programs, and business performance before and after the COVID-19 pandemic.[1]

The survey covers firms across all major sectors, which are grouped into five industry categories for sampling purposes: (1) Agriculture, Forestry, and Fishing; (2) Light Manufacturing 1 (e.g., food products); (3) Light Manufacturing 2 (e.g., wood products); (4) Heavy Manufacturing (e.g., machinery); and (5) Services.[2] The geographic scope includes both urban and rural areas in

[1] ERIA, requested by the ASEAN Secretariat following the decision made by the ASEAN Plus Three Consultations, conducted a questionnaire survey on the digital divide of MSMEs in the ASEAN Member States: Brunei Darussalam, Cambodia, Indonesia, the Lao People's Democratic Republic (Lao PDR), Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Viet Nam. The survey's primary purpose is to understand the actual conditions of relevant digital divide factors and how to overcome the obstacles MSMEs encounter to close the digital gaps among MSMEs in ASEAN. For further information about this survey, refer to Oikawa et al. (2024).

[2] Agriculture encompasses all relevant sub-industries of Agriculture, Forestry, and Fishing (US SIC 1987 codes 01–09). Light manufacturing 1 refers to relatively labor-intensive manufacturing industries producing consumables (USSIC 20–23). Light

each country, where the urban-rural classification follows the World Urbanization Prospects (United Nations, 2019).

The survey was administered by phone in order to capture micro and small firms more effectively and obtain information closer to on-the-ground conditions of the digital divide. A stratified sampling design was employed, targeting a predetermined number of observations in each segment defined by industry and urban/rural status. The sampling frame was constructed using the global firm database provided by D&B Hoovers, which compiles firm information from national business registries and other sources to provide firm-level attributes such as industry classification and company size. The target sample size was 3,000 firms (100 firms for each of the 10 segments × 3 countries).

A total of 18,601 firms were contacted, yielding 3,111 responses (response rate: 16.7%). After excluding incomplete responses, 3,099 valid observations remain. The survey was conducted between March 31 and July 7, 2023.

3.2 Surveyed Items

The survey measures adoption of 23 digital technologies—whether firms use them—and records the timing of adoption, distinguishing between technologies adopted before the COVID-19 pandemic (by 2019) and those adopted during the pandemic period (2020–2022).[3] These technologies are grouped into six functional categories according to their role in firm operations and production organization: foundational communication and computing tools, procurement tools, logistics tools, sales and marketing tools, operational infrastructure, and advanced technologies.

This classification reflects differences in how digital tools are used within firms, ranging from basic communication and administrative functions to integrated systems and production-level technologies. It allows us to capture variation in digitalization across business functions while maintaining a consistent framework for measuring overall digital adoption. Table 1 summarizes the classification and provides examples of technologies in each category.

The survey also records whether firms provide goods or services to, and/or procure from, MNFs; whether they received support for adopting digital tools from public and/or private sources; and whether their sales in 2022 increased, remained unchanged, or decreased relative to the pre-pandemic level in 2019.

Furthermore, the survey collects information on respondent firm characteristics, including firm size (number of employees), firm age, owner gender, owners' age and education levels.

4 Empirical Strategy

manufacturing 2 comprises other labor-intensive manufacturing industries (USSIC 24–27, 30, 31, and 34). Heavy manufacturing encompasses relatively capital-intensive manufacturing industries (USSIC 28, 29, 32, 33, and 35–38) and also includes Mining (10–14). Services encompass Finance, Insurance, and Real Estate (60–67), Other Services (70–89), and Public Administration (91–99).

[3] The original ERIA survey includes an item on email/chat applications within the foundational communication and computing tools category. This study excludes this item from the analysis. While email and chat applications are conceptually part of internal communication systems, their reported adoption rate is substantially lower than that of other tools in the same category. Discussions with the survey provider suggest that respondents may have interpreted this question as referring to regular business use rather than simple availability or occasional use. As a result, this variable likely captures a different margin of adoption and exhibits weak alignment with other tools in the category, potentially introducing measurement noise. For these reasons, we exclude this item from the analysis to preserve the interpretability of the category as a measure of firm-level digitalization.

4.1 Variable Construction

Firm-level technology adoption is inherently multidimensional, as firms typically use different technologies across multiple business functions. A small number of indicators—such as internet access or e-commerce participation—cannot fully capture the extent of digital adoption within firms. Recent research emphasizes the importance of measuring technology adoption across functional domains (Comin et al., 2025; Cireta, Comin, and Cruzz, 2022). While the Firm-level Adoption of Technology (FAT) framework discussed by Comin et al. (2025) evaluates technology sophistication at the task level, this study adopts a complementary approach by constructing a composite index that aggregates the adoption of multiple digital tools across business functions.

Specifically, we construct a standardized index of digital adoption following the aggregation approach used in the measurement of organizational capabilities (Bloom and Van Reenen, 2007). Each digital tool adoption indicator is standardized across firms and then aggregated to form a composite measure. This approach assigns relatively greater weight to less commonly adopted technologies and allows heterogeneous tools to contribute to a unified index. The resulting measure captures both the breadth of digital adoption within the firm and the relative sophistication of adopted tools.

While this index captures the breadth of adoption across technologies, it does not reflect how intensively these tools are used within firms. To complement this measure, we construct an indicator of digital adoption depth based on the share of employees engaged in digital-related tasks. This variable captures the degree to which digital technologies are embedded in firms' day-to-day operations and is standardized across firms to have mean zero and unit variance. Digital adoption breadth can be interpreted as capturing the extensive margin of digitalization, reflecting the range of technologies adopted, while digital adoption depth captures the intensive margin, reflecting how intensively these technologies are used within the firm.

In addition, the survey provides a self-reported measure of implementation effectiveness, which reflects firms' assessment of how successfully adopted digital tools have met their objectives and generated benefits. The measure is constructed by standardizing category-specific effectiveness indicators across firms, aggregating them at the firm level, and re-standardizing the resulting index. This allows the implementation effectiveness measure to be interpreted in terms of standard deviations, comparable to the digital adoption index.

4.1.1 Digital Adoption Breadth

We construct the digital adoption breadth index in three steps. First, we construct D_{il}^{z} by standardizing each digital tool l adoption dummy variable D_{il}, subtracting its sample mean $\overline{D}_l$, and dividing by its standard deviation, σ_l^D:

$$D_{il}^{z} = \frac{D_{il} - \overline{D}_l}{\sigma_l^D}.$$

Next, we aggregate D_{il}^{z}s across digital tools for each firm:

$$D_i^z = \sum_{l=1}^{24} D_{il}^z \,.$$

Finally, we standardize D_i^z to obtain the digital adoption breadth index:

$$DI_i = \frac{D_i^z - \overline{D^z}}{\sigma^{D^z}} \,.$$

The index has mean zero and unit variance. Coefficients therefore represent differences in digital adoption measured in standard deviations. Category-specific indices are constructed analogously.

4.1.2 Digital Adoption Depth

The digital adoption depth index is a standardized measure of digital adoption intensity based on the share of employees engaged in digital-related tasks. The original survey variable is reported in ordinal categories corresponding to the proportion of employees performing digital-related work. These categories are converted into an ordinal numerical measure and standardized across firms to have mean zero and unit variance. Although the index does not directly measure the sophistication of the underlying technologies or the intensity of digital use at the task level, it captures the share of employees engaged in digital-related activities and therefore provides an indicator of the extent to which digital technologies are embedded in firms' day-to-day operations. As such, it can be interpreted as the intensive margin of digitalization.

4.1.3 Implementation Effectiveness

The implementation effectiveness index is a standardized measure of firms' self-reported implementation effectiveness regarding adopted digital tools. The survey asks firms to evaluate implementation outcomes across six functional categories of digital tools. Category-specific effectiveness indicators are first standardized across firms, aggregated at the firm level, and then re-standardized to have mean zero and unit variance. The resulting index captures the extent to which firms perceive adopted digital technologies as successfully integrated into business operations and effective in achieving intended objectives.

4.1.4 Firm Resilience

Firm resilience is measured as the ability to maintain pre-pandemic performance. We define a binary indicator equal to one if firm sales in 2022 are at least as high as in 2019:

$$Resilience_i = \mathbf{1}\{Sales_{2022} \geq Sales_{2019}\}.$$

This measure captures whether firms were able to maintain or recover sales to at least pre-pandemic levels after a large negative shock. While it does not capture all dimensions of resilience, such as recovery speed or firm survival, sales recovery provides an observable and economically meaningful indicator of firms' ability to sustain economic activity during and after the COVID-19 disruption.

4.1.5 Local Peer Environment

Beyond firm-specific factors, diffusion theory highlights the role of the surrounding adoption environment. The information diffusion (epidemic) model emphasizes that firms may learn from prior adopters, as the prevalence of adoption reduces uncertainty and facilitates experimentation and imitation (Griliches, 1957; Goolsbee and Klenow, 2002; Conely and Udry, 2010). Empirical evidence suggests that industry environments and competitive conditions are associated with firm-level digitalization (Hollenstein, 2004).

At the same time, the stock model suggests that the returns to adoption may decline as technologies become more widely adopted, since competitive advantages diminish when adoption becomes widespread (Stoneman and Battisti, 2010). These mechanisms imply that the local adoption environment may be associated with firm-level digitalization through multiple channels, including learning, coordination, and competition.

To account for these influences, we construct peer-prevalence variables using leave-one-out (LOO) shares at the region–industry level:

$$P_{irk} = \frac{\sum_{j \neq i} Characteristic_{jrk}}{N_{rk} - 1},$$

where N_{rk} stands for the number of samples in each region (r)-industry (k) cell.

These variables measure the prevalence of firm characteristics—such as multinational linkages, support exposure, and digital adoption—among other firms in the same local production environment. By excluding the firm itself, the measure avoids mechanical correlation with the dependent variable.

Because the underlying mechanisms cannot be separately identified in our setting, these variables are interpreted as controls capturing the broader diffusion and competitive environment rather than isolating specific effects. They therefore serve to account for local conditions when estimating the association between firm-level characteristics and outcomes.

4.2 Econometric Specification

To examine the determinants of digital adoption, we estimate:

$$DI_i = \alpha + X_i'\beta + M_i'\gamma + S_i'\delta + P_{irk}'\theta + \mu_k + \mu_r + \varepsilon_i.$$

To examine the relationship between digitalization and resilience, we estimate:

$$Resilience_i = \alpha + \rho DI_i + X_i'\beta + M_i'\gamma + S_i'\delta + P_{irk}'\theta + \mu_k + \mu_r + \varepsilon_i.$$

The empirical specification includes four groups of variables: firm characteristics (X_i), multinational linkages (M_i), support exposure (S_i), and local peer environment (P_{irk}). While the analysis focuses on the associations of multinational linkages and support exposure with digitalization and firm performance, firm characteristics and peer variables are included to account for observable firm heterogeneity and local conditions.

Firm characteristics (X_i) include firm size (log employees), firm age, an indicator for post-

2020 entrants, and a rural location indicator. Because decision-making in MSMEs is concentrated in the owner-manager, we include owner characteristics—gender, age groups, and education levels—as proxies for managerial human capital. Multinational linkages (M_i) include indicators for whether the firm sells to multinational firms (MNF customers) and whether it sources inputs from them (MNF suppliers), capturing integration into global value chains. Support exposure (S_i) includes indicators for whether the firm has received public or private support. These variables capture exposure to advisory, financial, or institutional support systems. Peer environment (P_{irk}) includes the share of peer firms with MNF linkages, public support exposure, private support exposure, and digital adoption.

Industry fixed effects, μ_k, absorb sector-specific technology adoption and production characteristics, while region fixed effects, μ_r, control for local infrastructure, policy environment, and macroeconomic conditions common to firms operating in the same location. Standard errors are clustered at the regional level.

4.3 Lewbel IV Robustness

The baseline specifications estimate the relationships between firm characteristics, external linkages, support ecosystems, digital adoption, and resilience using ordinary least squares (OLS). However, some explanatory variables may be endogenous. In particular, the estimated relationships may be affected by omitted firm capabilities, self-selection, or reverse causality.

For the digital adoption regressions, firms linked to multinational customers or suppliers may possess unobserved managerial or organizational capabilities that facilitate both participation in GVCs and technology adoption. As a result, the estimated association between MNF linkages and digital adoption may partly reflect omitted firm capabilities rather than the effect of MNF linkages alone. Similarly, firms receiving public or private support may differ systematically from non-recipients because firms that are already interested in digitalization may be more likely to seek support. In addition, support providers may target firms that are already pursuing digitalization. These mechanisms give rise to both self-selection and reverse causality concerns.

For the resilience regressions, digital adoption may be correlated with unobserved managerial quality or organizational capabilities that independently contribute to firms' ability to withstand and recover from economic disruptions. Consequently, the estimated relationship between digital adoption and resilience may partly capture the influence of these unobserved capabilities.

To assess the robustness of the results to potential endogeneity, the analysis also employs the heteroskedasticity-based instrumental variable approach proposed by Lewbel (2012). This method generates internal instruments from exogenous covariates and can be applied when credible external instruments are unavailable. The Lewbel estimates are presented as a robustness check rather than the primary identification strategy.

5 Sample and Summary Statistics

This section describes the estimation sample and the main patterns in digital adoption prior to the regression analysis. Table 2 reports the composition of the sample, Table 3 presents adoption rates of individual digital tools, and Table 4 provides summary statistics for the variables used in the empirical analysis.

Because the empirical analysis examines peer environment effects defined at the region–industry level, observations belonging to cells with fewer than 10 firms are excluded in order to obtain stable leave-one-out measures of peer characteristics. After applying this restriction, the number of observations decreases from 3,099 valid survey responses to 2,864 firms. Regions correspond to subnational economic areas within each country (e.g., Sumatera, DKI Jakarta, Selangor, Red River Delta, Ho Chi Minh City).[4]

Table 2 shows that the sample consists primarily of micro and small enterprises. Firms with fewer than 20 employees account for the majority of observations in all three countries. The industrial distribution is balanced across the five targeted sectors—agriculture, two light manufacturing groups, heavy manufacturing, and services—reflecting the stratified sampling design. The geographic composition is also broadly comparable across countries, with both urban and rural firms represented.

Table 3 reports adoption rates by tool and category. Basic communication and computing technologies are widely adopted, while advanced tools such as artificial intelligence and robotics remain rare. Adoption rates differ substantially across categories, indicating large heterogeneity in digital adoption among MSMEs.

Adoption rates also vary across countries. For example, supplier EDI usage is relatively common in Indonesia but limited in Malaysia, while cybersecurity software and RFID are more prevalent in Indonesia and Viet Nam than in Malaysia. These differences suggest that firms operate within distinct technological environments, motivating the inclusion of region-level peer environment controls in the regression analysis.

Table 4 reports summary statistics for the variables used in the empirical analysis for two estimation samples. The full sample of 2,864 firms is used to examine the determinants of digital adoption, while the subsample of incumbent firms (N = 2,014) is used for the resilience regressions, which require pre-pandemic sales information.

Digitalization measures—breadth (adoption), depth (use intensity), and implementation effectiveness—are standardized to have mean zero and unit variance in the full sample. The resilience indicator is defined only for incumbent firms and equals one if a firm's sales in 2022 are at least as high as in 2019; approximately 34 percent of incumbent firms meet this condition.

The data reveal substantial cross-firm heterogeneity in firm characteristics. Firms differ in size and age, with both newly established and long-operating enterprises represented. Owner characteristics also display considerable dispersion in education and age, consistent with heterogeneity in managerial human capital emphasized in the firm capability hypothesis.

There is similarly notable variation in firms' external linkages and support exposure. Only a subset of firms is connected to multinational firms, and support receipt—particularly public support—is limited, suggesting uneven access to external resources.

Finally, peer environment variables exhibit meaningful dispersion across region–industry cells. These variables capture differences in local digital adoption, multinational presence, and support exposure, indicating that firms operate in heterogeneous local environments.

6 Results

[4] The list of regions that we used for regressions are: (Indonesia) Sumatera; DKI Jakarta; Jawa Barat; Jawa Tengah; Jawa Timur; Banten; Bali & Nusa Tenggara; Kalimantan; Sulawesi, Maluku & Papua; (Malaysia) Johor; Pahang; Perak; Pulau Pinang; Sabah; Sarawak; Selangor; W.P. Kuala Lumpur; (Viet Nam) Northern Midlands and Mountains; Red River Delta; Hanoi; North Central and Central Coast; Central Highlands; South East; Ho Chi Minh City; Mekong River Delta.

6.1 Determinants of Digital Adoption

Table 5 presents the baseline results for the determinants of digital adoption breadth. Overall, the results are consistent with the firm capability hypothesis (H1), which predicts that firms with stronger internal resources and organizational capability exhibit higher levels of digital adoption breadth.

Firm characteristics are strongly associated with digital adoption breadth. Firm size is positively and robustly associated with digital adoption breadth across all specifications (models 1–4), indicating that larger firms adopt a wider range of digital tools. In contrast, firms established after 2020 exhibit significantly lower digital adoption breadth across all specifications, suggesting that newly established firms have not yet accumulated the organizational capacity required for broad digital adoption.

Owner characteristics also play an important role. Compared with the youngest age group, firms managed by middle-aged owners exhibit substantially higher digital adoption breadth (models 1–4), while the association weakens for older owner groups. Female-owned firms are consistently more digitally intensive across specifications. Education is positively associated with digital adoption breadth for high school and university education levels, although the differences across higher academic categories are relatively modest. Vocational education, by contrast, is negatively associated with digital adoption breadth, indicating that the type of human capital—rather than its level alone—may be more relevant for broad digital adoption.

The inclusion of multinational linkages in model 2 substantially improves explanatory power. Both MNF customer and supplier linkages are strongly and positively associated with digital adoption breadth in models 2–4, with coefficients around 0.4 standard deviations. These results provide strong support for the network integration hypothesis (H2), indicating that firms integrated into multinational production and customer networks tend to adopt a broader set of digital tools.

By contrast, support variables in model 3 are not significantly associated with adoption breadth, suggesting that support exposure is not strongly related to the extensive margin of digital adoption.[5] The inclusion of peer variables in model 4 does not materially alter the coefficients on firm characteristics or multinational linkages, although peer private-support prevalence exhibits a weak negative association with adoption breadth.

Table 6 examines digitalization in terms of digital adoption depth. Several patterns differ from the adoption-breadth results. Firm size remains strongly positive across all specifications (models 1–4), but the magnitude is substantially larger, indicating that larger firms not only adopt more digital tools but also use them more intensively. In contrast to the breadth results, support variables are strongly and positively associated with digital adoption depth. Both public and private support exhibit positive and statistically significant associations in models 3 and 4, providing support for the support hypothesis (H3), particularly along the intensive margin of digitalization. Multinational linkages also remain positively associated with digital adoption depth in models 2–4, although the magnitude is somewhat smaller than in the adoption-breadth regressions.

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[5] Additional results by tool category (reported in Appendix Table A.1) provide further nuance. While support exposure is not significantly associated with digital adoption breadth, the category-level estimates suggest that support is positively associated with the adoption of specific tools, particularly those related to sales management and operational infrastructure. At the same time, support is negatively associated with more basic tools. These patterns indicate that the role of support may differ across functional domains, even though its overall association with broad adoption is limited. Consistent with the main results, this suggests that support programs may be more closely related to the depth of use and implementation of digital technologies rather than to broad adoption across all tool categories.

Table 7 reports results for implementation effectiveness. Firm size is positively associated with implementation effectiveness across specifications (models 1–4), although the magnitude is smaller than for adoption breadth or adoption depth. Newly established firms again exhibit substantially lower implementation effectiveness, indicating weaker implementation outcomes among younger firms.

A notable difference is that higher levels of formal education are negatively associated with implementation effectiveness relative to the baseline education category, while vocational education exhibits a particularly strong negative association. One possible interpretation is that the self-reported nature of the IE measure introduces systematic differences in reporting behavior: more educated managers may apply stricter evaluation standards when assessing implementation outcomes. These results should therefore be interpreted cautiously, as they may partly reflect reporting behavior rather than underlying implementation quality.

Both multinational linkages and support exposure are positively associated with implementation effectiveness, again broadly consistent with H2 and H3. In particular, public support exhibits a strong positive association in models 3 and 4, suggesting that support programs may play an important role in improving implementation outcomes even if they are less strongly associated with adoption breadth itself.

6.2 Lewbel IV Robustness for Digitalization Outcomes

Table 8 reports instrumental variable estimates using the heteroskedasticity-based identification strategy proposed by Lewbel (2012). Following conventional IV practice, the KP LM statistic is used to assess underidentification, the KP Wald F-statistic is used to assess weak instruments, and the Hansen J-statistic is used to evaluate overidentifying restrictions. The OLS results suggest that multinational linkages are positively associated with digital adoption breadth, while support exposure is more strongly related to digital adoption depth and implementation effectiveness.

The reliability of the Lewbel specifications differs across regressions. Among the multinational linkage specifications, the customer-linkage regressions for adoption breadth, adoption depth, and implementation effectiveness (models 1, 5, and 9) exhibit comparatively stronger identification diagnostics. In particular, the KP LM statistics come closest to conventional significance levels for rejecting underidentification among the multinational-linkage specifications, the KP Wald F-statistics exceed the conventional rule-of-thumb threshold of 10 for weak instruments, and the Hansen J-statistics do not reject instrument validity. The estimated coefficients also remain positive across all three specifications. Collectively, these results suggest that the positive association between multinational customer linkages and digitalization outcomes is relatively robust to endogeneity concerns.

By contrast, the supplier-linkage regressions (models 2, 6, and 10) display weaker identification diagnostics, particularly with respect to the KP Wald F-statistics. Although the estimated coefficients remain positive in models 2 and 6, the weaker first-stage diagnostics imply that these results should be interpreted more cautiously.

The support-related regressions also provide relatively consistent evidence. Considering first the public-support specifications (models 3, 7, and 11), the identification diagnostics are relatively favorable, particularly for adoption depth and implementation effectiveness (models 7 and 11). While the KP LM statistics do not reject underidentification at conventional significance levels, the KP Wald F-statistics exceed conventional weak-instrument thresholds and the Hansen J-statistics do not reject instrument validity. The estimated coefficients remain positive, and their statistical significance is consistent with the corresponding OLS results.

The estimated coefficients for private support (models 4, 8, and 12) remain positive across all three outcomes. However, the KP Wald F-statistics do not consistently exceed the conventional rule-of-thumb threshold of 10 for weak instruments, suggesting that weak-instrument concerns cannot be ruled out. The relatively large IV coefficients compared with the corresponding OLS estimates are consistent with this interpretation. Although the Hansen J-statistics do not reject instrument validity, the weaker identification diagnostics warrant cautious interpretation of the private-support estimates.

Overall, the Lewbel estimates provide the most consistent support for the OLS findings related to public support, particularly for digital adoption depth and implementation effectiveness. These specifications exhibit positive and statistically significant coefficients together with comparatively favorable identification diagnostics. The results for multinational customer linkages are also broadly consistent with the OLS estimates, with positive coefficients across outcomes and comparatively stronger diagnostic performance than other multinational-linkage specifications. By contrast, the evidence for multinational supplier linkages is less conclusive because the estimated coefficients remain positive but the identification diagnostics are generally weaker. Similarly, although private support remains positively associated with digitalization outcomes, the relatively large IV coefficients and weaker diagnostic performance suggest that these estimates should be interpreted more cautiously. Collectively, the Lewbel results provide the most consistent support for public support and multinational customer linkages as correlates of digitalization outcomes, while offering more limited evidence regarding multinational supplier linkages and private support.

6.3 Digital Adoption and Firm Resilience

Table 9 presents the baseline results for the association between digital adoption breadth and firm resilience during the COVID-19 period. Consistent with the resilience hypothesis (H4), digital adoption breadth is positively associated with resilience in the baseline specification (model 1). A one-standard-deviation increase in digital adoption breadth is associated with a higher probability of maintaining non-negative sales performance relative to the pre-pandemic period.

However, the magnitude and statistical significance of the coefficient vary across specifications. After controlling for multinational linkages (model 2), the coefficient declines and becomes statistically insignificant, suggesting that part of the baseline relationship reflects differences in global value chain integration. The coefficient becomes statistically significant again after incorporating peer variables (model 4), indicating that local business environments shape the relationship between digitalization and resilience.

Support variables are strongly and positively associated with resilience in models 3 and 4, while peer digital adoption prevalence exhibits a robust negative association in model 4. This negative coefficient suggests that the relative advantage of digitalization may diminish in more digitally intensive local environments, consistent with the idea that the benefits of digital adoption become less differentiated as adoption becomes more widespread.

Table 10 examines heterogeneity across digital tool categories. The results reveal substantial differences across functions. Sales and marketing tools and operational infrastructure (models 4 and 5) exhibit strong positive associations with resilience, indicating that customer-facing systems and operational digital infrastructure were particularly important for adaptation during the

COVID-19 shock. Advanced technologies also display a positive association with resilience (model 6). By contrast, foundational communication tools and logistics tools (models 1 and 3) are negatively associated with resilience, suggesting that these more basic or coordination-oriented technologies were less directly related to adaptive responses during prolonged disruptions. Procurement-related tools exhibit only weak positive associations (model 2). These findings indicate that the relationship between digitalization and resilience depends substantially on the functional role of technologies rather than on digital adoption in general.

Table 11 reports results using digital adoption depth rather than adoption breadth. In contrast to the breadth measure, digital adoption depth remains strongly and consistently associated with resilience across all specifications (models 1–4). A one-standard-deviation increase in digital adoption depth is associated with a substantially higher probability of maintaining pre-pandemic sales performance. Compared with the adoption-breadth results in Table 9, these findings suggest that digital adoption depth is more strongly associated with resilience than the breadth of adoption alone. Together with the implementation-effectiveness results discussed earlier, the evidence indicates that the resilience benefits of digitalization operate primarily through effective utilization and implementation rather than through broad adoption itself.

As a robustness check, Appendix Tables A.2 and A.3 report estimates using pre-pandemic measures of digital adoption breadth constructed only from technologies adopted before 2020. These specifications help address concerns that the baseline estimates may partly capture reactive adoption during the COVID-19 period. The results remain broadly consistent with the main findings. Pre-pandemic digital adoption breadth continues to exhibit positive associations with resilience overall, while sales and marketing tools and operational infrastructure remain positively associated with resilient firm performance. By contrast, foundational communication and logistics tools continue to display weaker or negative relationships. These findings reinforce the interpretation that pre-existing customer-facing and operational digital adoption was particularly important for adjustment during large disruptions.

6.4 Lewbel IV Robustness for Firm Resilience

Table 12 reports Lewbel IV estimates for the relationship between digital adoption and firm resilience during the COVID-19 period. The OLS results indicate that digitalization is positively associated with resilience overall, although the relationship differs substantially across digital functions. In particular, sales and marketing tools, operational infrastructure, advanced technologies, and digital adoption depth exhibit the strongest positive associations with resilient firm performance in the OLS regressions (Table 10, columns 4–6; Table 11).

The reliability of the Lewbel specifications varies across categories. Among the more favorable specifications, the regressions for sales and marketing tools, operational infrastructure, advanced technologies, and digital adoption depth (models 5–8) exhibit comparatively stronger identification diagnostics. In particular, the KP Wald F-statistics exceed the conventional rule-of-thumb threshold of 10 for weak-instruments, while the Hansen J statistics do not reject instrument validity. The coefficients for these specifications also remain positive and statistically significant. Collectively, these results provide relatively consistent support for the OLS finding that customer-facing technologies, operational systems, advanced digital tools, and intensive digital use are positively associated with resilience during the COVID-19 shock.

The evidence is weaker for the overall adoption index and several more basic tool categories. The overall adoption index (model 1) remains positive and marginally significant, although the

KP Wald F-statistic is relatively modest, suggesting that the estimated relationship should be interpreted with some caution. The procurement specification (model 3) also exhibits a reasonably strong KP Wald F-statistic, but the coefficient remains statistically insignificant. By contrast, the foundational communication specification (model 2) displays particularly weak identification diagnostics, including limited evidence against underidentification and weak-instrument concerns, implying that the estimated relationship should be interpreted cautiously. The logistics specification (model 4) exhibits comparatively stronger identification diagnostics, but the coefficient remains close to zero and statistically insignificant.

Overall, the Lewbel estimates most consistently support the OLS findings for sales and marketing tools, operational infrastructure, advanced technologies, and digital adoption depth. The results therefore suggest that the positive association between digitalization and resilience is most consistently observed for customer-facing technologies, operational systems, advanced digital tools, and intensive digital use rather than for broad digital adoption alone.

7 Discussion and Policy Implications

The results highlight three main themes: the role of organizational capacity in shaping digitalization, the importance of distinguishing between the adoption and use of digital technologies, and the conditions under which digitalization contributes to firm resilience. Together, these findings provide new evidence on how digitalization operates in MSMEs and how policy can support effective digital transformation.

The results show that digitalization among MSMEs is primarily associated with underlying organizational and managerial capacity rather than simple access to technology. Both owner education and owner age are positively associated with digitalization, suggesting that managerial experience and accumulated human capital contribute to firms' ability to adopt and integrate digital tools. Newly established firms also display substantially lower levels of adoption, while conditional on post-2020 entry status, firm age itself is only weakly associated with digital adoption. Taken together, these findings suggest that differences in digitalization across MSMEs are driven less by accumulated operational experience at the firm level than by differences in managerial capability and the ability to organize, implement, and integrate digital technologies within the firm. These findings are consistent with rank-based adoption models (Stoneman and Battisti, 2010), in which heterogeneous returns to adoption arise from differences in firms' organizational and managerial capacity. They also align with qualitative evidence emphasizing that successful digitalization depends not only on technology access, but also on the integration of digital tools with organizational routines, managerial capabilities, and operational processes within firms (Ferreira et al., 2025; Kallmuenzer et al., 2025).

More specifically, the results suggest that the relationship between managerial human capital and digitalization is not strongly increasing at higher levels of formal education. Consistent with prior literature (e.g., Bartel and Lichtenberg, 1987), education is positively associated with digital adoption relative to low-education groups. However, the estimated effects for high school, university, and graduate education are similar in magnitude. This pattern suggests that, in the context of increasingly standardized and widely available digital technologies, the marginal contribution of additional formal education beyond baseline managerial competence may be limited for adoption decisions among MSMEs. Combined with the positive association between owner age and digitalization, the results instead point to the broader importance of practical managerial capability and implementation experience in shaping firms' ability to integrate digital tools into business operations (McKenzie and Woodruff, 2017).

Separately, the results highlight the importance of external production linkages. While prior studies document that GVC participation is associated with technology upgrading in developing economies (e.g., Delera et al., 2022, Atkin, Khandelwal and Osman, 2017), this paper finds that customer-side multinational linkages are positively associated with digitalization across multiple dimensions, including adoption breadth, adoption depth, and implementation effectiveness. The evidence for supplier linkages is generally positive but less conclusive. This pattern indicates that integration into GVCs not only encourages firms to adopt a wider range of digital tools, but also promotes their effective use and integration into business operations.

A different pattern emerges for support exposure. Support exposure, particularly public support, is more strongly associated with the intensive margin of digitalization—adoption depth and implementation effectiveness—than with broad adoption across tools. This difference indicates that external linkages and support programs are associated with distinct dimensions of digitalization. While multinational linkages appear to shape both adoption and use through coordination requirements and market pressures, support programs are more closely related to how technologies are used within firms. This interpretation is consistent with policy-oriented work (e.g., Oikawa et al., 2024), which emphasizes capability building—such as training, advisory services, and digital workflow adaptation—rather than equipment subsidies.

The resilience analysis provides complementary insights into the role of digitalization during large shocks. Several dimensions of digitalization are positively associated with maintaining sales during the COVID-19 period, particularly customer-facing tools, operational infrastructure, advanced technologies, and digital adoption depth. These associations remain when digital adoption is measured using pre-pandemic adoption, indicating that the results are not driven solely by reactive digitalization during the crisis. Existing studies on digitalization and resilience during COVID-19 primarily focus on specific technologies, particularly market-interface tools such as e-commerce and digital platforms. For example, Li et al. (2023) show that participation in third-party e-commerce platforms improved resilience among Chinese retail firms, while Oikawa et al. (2025a, 2025b) document that online sales tools helped MSMEs in Southeast Asia adapt to lockdown conditions over time (Calza et al., 2023). In contrast, this paper shows that pre-existing digital capabilities across multiple business functions—rather than the adoption of a single tool—are associated with firm performance during large disruptions.

At the same time, the magnitude of the resilience effect varies across dimensions of digitalization. Digital adoption breadth (extensive margin) shows a positive but modest association, while digital adoption depth (intensive margin) is more strongly and consistently associated with resilience. This indicates that the benefits of digitalization depend more on how intensively technologies are used within firms than on the breadth of adoption alone. Category-level results provide supporting evidence for this interpretation: tools related to customer interaction and operational coordination tend to exhibit stronger associations with resilience. Overall, these findings suggest that digitalization in MSMEs is not merely a technology adoption process, but a capability-driven transformation whose economic benefits depend on effective use and integration.

The results also provide suggestive evidence consistent with stock-model logic in the diffusion literature. The negative association between peer digital adoption prevalence and resilience indicates that the relative advantage of digitalization declines as adoption becomes more widespread. This pattern is consistent with the idea that early adopters benefit from temporary advantages that erode as technologies diffuse and become standard business practice (Stoneman and Battisti, 2010). In the stock model, returns to adoption decline as the number of adopters increases due to imitation and competition—an effect often referred to as order effects. A similar argument in the management literature suggests that the diffusion of best practices leads to competitive convergence (Porter, 2001). While not directly identified, the observed pattern aligns with these theoretical predictions and highlights the importance of the surrounding diffusion environment.

Several policy implications follow. First, digitalization policies should prioritize capability formation, including managerial skills, organizational processes, and the effective use of digital tools. The results indicate that internal organizational capacity is a key determinant of both adoption and resilience outcomes. Second, policies that facilitate MSME participation in global value chains, particularly through linkages with multinational customers, may be particularly effective. Firms appear to adopt digital tools in response to coordination and reporting requirements imposed by external partners, suggesting that network integration can serve as a catalyst for digital upgrading. Third, policy design should recognize that different digital tools serve different functions. Technologies that support customer interaction and operational coordination appear particularly important for resilience, while tools primarily associated with routine administrative functions may have more limited effects in crisis contexts. Fourth, from the perspective of reducing the digital divide, attention should focus on technologies that remain relatively underused but have strong associations with performance, particularly market-interface tools such as e-commerce, digital payments, and customer management systems.

Finally, several limitations should be noted. The analysis is based on self-reported survey data, which may be subject to measurement and reporting biases, particularly for implementation effectiveness. In addition, because the survey covers only firms that remained in operation at the time of the survey, the resilience analysis may be affected by survivorship bias. Firms that exited during the COVID-19 period are not observed, and if less digitally capable firms were more likely to fail, the estimated relationship between digital adoption and resilience may understate the association between digitalization and resilient sales performance during the pandemic. While the use of pre-pandemic adoption measures and Lewbel IV estimates provides robustness, the results should be interpreted as associations rather than definitive causal effects. More broadly, the digital landscape is evolving rapidly. The increasing adoption of generative AI and other advanced digital technologies may alter both the nature of digital capability and the mechanisms through which digitalization affects firm performance. Unlike earlier digital tools, generative AI has the potential to directly augment cognitive tasks and reduce the importance of certain types of managerial input. As such technologies diffuse, the relationship between human capital, digital adoption, and firm performance may change in ways not captured in the current data. Future research should therefore examine how emerging technologies reshape the digitalization process, particularly for MSMEs in developing economies.

8 Conclusion

This paper examines the determinants and consequences of digital adoption among MSMEs in Southeast Asia. Using firm-level survey data from Indonesia, Malaysia, and Viet Nam, the analysis distinguishes between the adoption stage—why some firms digitalize more extensively and intensively than others—and the performance stage—whether digitalization is associated with resilience during a large aggregate shock.

Three main findings emerge. First, digital adoption reflects underlying organizational capacity rather than a simple technology acquisition decision. Firms with stronger managerial human capital and greater participation in GVCs, particularly through customer linkages, exhibit substantially higher digital adoption, while newly established firms display markedly lower adoption. Peer and support effects are more selective and operate through different dimensions of digitalization. These patterns are consistent with rank-based diffusion mechanisms (Stoneman and Battisti, 2010), in which heterogeneous expected returns—driven by managerial capability and external linkages—shape adoption outcomes. Digitalization is therefore embedded in broader organizational and relational structures rather than diffusing uniformly across firms.

Second, several dimensions of digitalization are positively associated with resilience during the COVID-19 shock. Firms with higher adoption of sales and marketing technologies, operational infrastructure, advanced technologies, and higher digital adoption depth were more likely to maintain sales relative to the pre-crisis period. This relationship remains when digital adoption is measured using pre-pandemic adoption, indicating that the results are not driven solely by reactive digitalization. Importantly, the magnitude of the effect varies substantially across dimensions of digitalization. A central finding of the paper is that digital adoption depth is more strongly and consistently associated with resilience than adoption breadth alone. This suggests that the economic benefits of digitalization depend less on the number of technologies adopted than on how effectively digital tools are utilized and integrated into firm operations. Category-level evidence further indicates that customer-facing systems and operational infrastructure are particularly important for resilience during large disruptions.

Third, the resilience premium associated with digital adoption declines in more digitally intensive environments. Where surrounding firms are already highly digitalized, the marginal advantage of digital adoption is smaller. This pattern is consistent with stock diffusion logic: early adopters benefit from temporary advantages, but these advantages dissipate as technologies diffuse and become standard practice (Stoneman and Battisti, 2010; Porter, 2001). Digitalization thus functions as a source of competitive advantage when scarce but increasingly becomes a baseline requirement as adoption spreads.

Collectively, these findings suggest that the digital divide among MSMEs is fundamentally a capability divide. Access to digital tools alone is insufficient; effective digitalization depends on managerial capacity, organizational adaptation, and integration into business networks. Moreover, while digitalization is associated with improved resilience, its benefits depend on the intensity of use, the stage of diffusion, and the functional role of technologies.

These findings have several implications for development policy. First, digitalization strategies should prioritize capability formation, including managerial skills, workflow redesign, and business process upgrading. Second, facilitating MSME participation in GVCs, particularly through linkages with multinational customers, can serve as an effective channel for digital upgrading, as business relationships embed coordination and reporting requirements that incentivize adoption and use. Third, policy design should recognize that not all digital technologies contribute equally to performance. From the perspective of reducing the digital divide, attention should focus on promoting the effective use of underutilized but operationally relevant technologies—such as e-commerce, digital payments, and customer management systems—rather than on expanding access alone.

This study also highlights several directions for future research. While the analysis documents robust associations between digital adoption and resilience, establishing causal effects would require panel data or experimental designs. Further work could examine longer-term productivity dynamics, the role of financial constraints in digital investment, and cross-country institutional differences in diffusion patterns. In addition, the rapid emergence of generative AI and related technologies may alter the nature of digital capability and the mechanisms through which digitalization affects firm performance. As such technologies diffuse, the relationship between human capital, digital adoption, and economic outcomes may evolve in ways not captured in the current data.

Overall, digitalization among MSMEs emerges as a capability-driven and diffusion-dependent process. Its benefits are meaningful but contingent on organizational readiness and competitive context. Bridging the digital divide therefore requires sustained investment in managerial capability, organizational adaptation, and participation in digital and GVCs, ensuring that digital transformation supports broad-based and resilient development.

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Table 1. Classification of Digital Technologies

Category	Description	Surveyed tools
Foundational communication and computing tools (FC)	Basic tools for internal communication and administration	Mobile devices, computers, office suite (e.g., Word, Excel, PowerPoint), web meeting systems
Procurement tools (PR)	Tools supporting transactions with suppliers	Supplier EDI, electronic payments
Logistics tools (LG)	Tools for managing inventory and delivery processes	Document/cargo delivery application, storage/inventory management systems
Sales and marketing tools (SM)	Tools for customer interaction and market access	Customer EDI, SNS, E-commerce, customer electronic payments, sales management tools
Operational infrastructure (OI)	Firm-wide systems integrating operations and data	ERP, cloud storage/centralized server, cybersecurity/protection software
Advanced technologies (AT)	Frontier technologies affecting production and automation	3D printing, AI, AR, drones, IoT device, RFID, robotics

Notes: EDI = Electronic Data Interexchange. SNS = Social Networking Service. ERP = Enterprise Resource Planning. AI = Artificial Intelligence. AR = Augmented Reality. IoT = Internet-of-Things. RFID = Radio Frequency Identification.
Source: Oikawa et al. (2024) and authors' elaboration.

Table 2. Firm size, industry, and location composition of the sample

	Indonesia		Malaysia		Viet Nam	
	N	Pct	N	Pct	N	Pct
Firm size (number of employees)						
1-4 employees	125	0.13	92	0.10	430	0.42
5-9 employees	227	0.24	202	0.23	391	0.38
10-19 employees	502	0.53	453	0.51	187	0.18
20-49 employees	88	0.09	147	0.16	20	0.02
Industry						
Agriculture, Foresty, Fishing	186	0.20	185	0.21	211	0.21
Light manufacturing 1 (food products etc.)	185	0.20	177	0.20	221	0.21
Light manufacturing 2 (wood products etc.)	196	0.21	175	0.20	201	0.20
Heavy manufacturing (machineries etc.)	179	0.19	168	0.19	200	0.19
Services	196	0.21	189	0.21	195	0.19
Location						
Urban area	485	0.51	329	0.37	452	0.44
Rural area	457	0.49	565	0.63	576	0.56

Sample size: Indonesia = 942; Malaysia = 894; Viet Nam = 1028.

Notes: Agriculture encompasses all relevant sub-industries of Agriculture, Forestry, and Fishing (US SIC 1987 codes 01–09). Light manufacturing 1 refers to relatively labor-intensive manufacturing industries producing consumables (USSIC 20–23). Light manufacturing 2 comprises other labor-intensive manufacturing industries (USSIC 24–27, 30, 31, and 34). Heavy manufacturing encompasses relatively capital-intensive manufacturing industries (USSIC 28, 29, 32, 33, and 35–38) and also includes Mining (10–14). Services encompass Finance, Insurance, and Real Estate (60–67), Other Services (70–89), and Public Administration (91–99). The urban-rural classification is derived from the World Urbanization Prospects (United Nations, 2019).

Source: Authors' calculations.

Table 3. Adoption Rates of Digital Tools by Category and Country

	All	Indonesia	Malaysia	Viet Nam
Foundational communication and computing tools (FC)				
FC1: Mobile device	0.82	0.88	0.54	1.00
FC2: Computer	0.88	0.99	0.62	1.00
FC3: Office suite	0.40	0.39	0.28	0.51
FC4: Web meeting system	0.00	0.00	0.00	0.00
All FC tools	0.52	0.57	0.36	0.63
Procurement tools (PR)				
PR1: EDI with suppliers	0.23	0.40	0.06	0.24
PR2: E-payment to suppliers	0.68	0.64	0.59	0.79
All PR tools	0.46	0.52	0.32	0.51
Logistics tools (LG)				
LG1: Document/cargo delivery application	0.53	0.46	0.41	0.69
LG2: Storage/inventory management system	0.22	0.32	0.21	0.14
All LG tools	0.37	0.39	0.31	0.41
Sales and marketing tools (SM)				
SM1: EDI with customers	0.18	0.27	0.05	0.22
SM2: SNS	0.31	0.42	0.24	0.28
SM2: E-commerce	0.24	0.40	0.05	0.26
SM4: E-payment from customers	0.29	0.36	0.18	0.30
SM5: Sales management tools	0.08	0.18	0.03	0.03
ALL SM tools	0.22	0.32	0.11	0.22
Operational infrastructure (OI)				
OI1: ERP	0.09	0.15	0.01	0.10
OI2: Cloud storage/centralized server	0.05	0.09	0.05	0.02
OI3: Cybersecurity/protection software	0.52	0.71	0.30	0.53
All OI tools	0.22	0.32	0.12	0.22
Advanced digital tools (AT)				
AT1: 3D printing	0.07	0.10	0.04	0.05
AT2: Artificial intelligence (AI)	0.01	0.01	0.00	0.00
AT3: Augmented reality (AR)	0.00	0.00	0.00	0.00
AT4: Drone (e.g. farming management)	0.00	0.01	0.00	0.00
AT5: Internet-of-Thing (IoT) device	0.11	0.08	0.21	0.05
AT6: Radio frequency identification (RFID)	0.41	0.59	0.10	0.50
AT7: Robotics (e.g. factory robots)	0.03	0.07	0.00	0.03
All AT tools	0.07	0.11	0.02	0.08
All Digital tools (ALL)	0.26	0.32	0.16	0.29

Notes: EDI = Electric Data Interexchange. ERP = Enterprise Resource Planning. All pools the three countries. Category rows show the average adoption rate within each tool category.
Source: Authors' calculations.

Table 4. Summary Statistics of Variables Used in the Empirical Analysis

	All firms (N=2864)		Incumbent firms (N=2014)	
	Mean	SD	Mean	SD
Panel A: Digital adoption, effectiveness, and performance				
Adoption breadth (overall digital tool adoption)	0.00	1.00	0.03	1.12
Adoption depth (digital workforce share)	0.00	1.00	0.20	0.96
Implementation effectiveness	0.00	1.00	0.16	0.91
Robust sales performance (2022 >= 2019)	N.A.	N.A.	0.34	0.47
Panel B: Firm characteristics				
Log employees	2.22	0.74	2.41	0.68
Post-2020 entrant	0.30	0.46	0.00	0.00
Rural area	0.56	0.50	0.56	0.50
Firm age	15.87	13.20	21.29	12.19
Owner age 26-41	0.29	0.46	0.21	0.40
Owner age 42-57	0.49	0.50	0.52	0.50
Owner age 58-76	0.20	0.40	0.26	0.44
Owner age 77-	0.01	0.07	0.01	0.09
Female owner	0.11	0.31	0.08	0.27
Owner: High school	0.20	0.40	0.18	0.39
Owner: Vocational school	0.04	0.19	0.02	0.13
Owner: University	0.39	0.49	0.41	0.49
Owner: Graduate degree	0.22	0.41	0.23	0.42
Panel C: Multinational linkages and support				
MNF customer linkage	0.28	0.45	0.33	0.47
MNF supplier linkage	0.26	0.44	0.28	0.45
Public support receipt	0.06	0.23	0.08	0.27
Private support receipt	0.33	0.47	0.40	0.49
Panel D: Peer environment				
Peer MNF linkage prevalence	0.40	0.11	0.41	0.11
Peer public support prevalence	0.06	0.07	0.08	0.07
Peer private support prevalence	0.33	0.15	0.37	0.15
Peer overall digital tool adoption	0.26	0.07	0.25	0.08

Notes: Panel columns report means and standard deviations for the full sample and for the incumbent-firm sample used in the performance regressions. Digital adoption measures (breadth and depth) and implementation effectiveness are standardized to have mean zero and unit variance in the full sample. Peer prevalence variables are leave-one-out shares of other firms in the same region-industry cell exhibiting the corresponding characteristic. Public support and private support indicate whether the firm has ever received assistance and do not capture timing. The resilient sales performance indicator equals one if sales in 2022 are non-negative relative to 2019.
Source: Authors' calculations.

Table 5. Determinants of Digital Adoption Breadth

Dependent variable: Digital adoption breadth

	(1) Baseline	(2) +MNF	(3) + Support	(4) +Peer
Firm characteristics:				
Log employees	0.142***	0.128***	0.129***	0.120***
	(0.025)	(0.023)	(0.024)	(0.021)
Post-2020 entrant	-0.506***	-0.385***	-0.391***	-0.393***
	(0.057)	(0.052)	(0.045)	(0.044)
Rural area	-0.076	-0.039	-0.043	-0.055
	(0.057)	(0.069)	(0.066)	(0.069)
Firm age	0.004	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Owner age 26-41	1.275***	1.370***	1.388***	1.353***
	(0.186)	(0.212)	(0.209)	(0.212)
Owner age 42-57	1.285***	1.370***	1.392***	1.357***
	(0.182)	(0.204)	(0.197)	(0.201)
Owner age 58-76	0.970***	1.043***	1.073***	1.053***
	(0.251)	(0.272)	(0.250)	(0.257)
Owner age 77-	0.333	0.445	0.486	0.482
	(0.263)	(0.292)	(0.302)	(0.312)
Female owner	0.308***	0.277***	0.281***	0.269***
	(0.066)	(0.066)	(0.067)	(0.066)
Owner: High school	0.358***	0.276***	0.276***	0.279***
	(0.079)	(0.058)	(0.057)	(0.056)
Owner: Vocational school	-0.205*	-0.298**	-0.287**	-0.263**
	(0.112)	(0.110)	(0.119)	(0.121)
Owner: University	0.339***	0.219**	0.227**	0.234**
	(0.110)	(0.096)	(0.102)	(0.106)
Owner: Graduate degree	0.368***	0.233**	0.239**	0.254**
	(0.113)	(0.107)	(0.113)	(0.122)
Multinational linkages				
MNF customer linkage		0.412***	0.423***	0.427***
		(0.059)	(0.073)	(0.073)
MNF supplier linkage		0.411***	0.414***	0.413***
		(0.077)	(0.083)	(0.081)
Support exposure:				
Public support receipt			-0.087	-0.065
			(0.122)	(0.113)
Private support receipt			-0.044	-0.036
			(0.093)	(0.089)
Peer environment:				
Peer MNF linkage prevalence				0.128
				(0.174)
Peer public support prevalence				-0.462
				(0.419)
Peer private support prevalence				-0.327*
				(0.188)
Peer digital adoption prevalence				1.737
				(1.065)
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
N	2864	2864	2864	2864
R-squared	0.339	0.422	0.423	0.428

Note: * p<0.10, ** p<0.05, *** p<0.01. The dependent variable is a standardized digital adoption index constructed by aggregating adoption across digital tools and normalizing to mean zero and unit variance. For each digital tool, adoption indicators are standardized across firms, summed within firm, and the sum is standardized again to have mean zero and unit variance. Coefficients therefore represent differences in digital adoption measured in standard deviations. Peer prevalence variables are constructed as leave-one-out shares of other firms in the same region-industry cell exhibiting the corresponding characteristic. The omitted owner education category is middle school or less, and the omitted owner age category is 18-25. Standard errors (in parentheses) are clustered at the region level.
Source: Authors' calculations.

Table 6. Determinants of Digital Adoption Depth

Dependent variable: Digital adoption depth

	(1) Baseline	(2) +MNF	(3) + Support	(4) +Peer
Firm characteristics				
Log employees	0.472***	0.458***	0.452***	0.461***
	(0.022)	(0.023)	(0.023)	(0.024)
Post-2020 entrant	-0.782***	-0.675***	-0.642***	-0.640***
	(0.105)	(0.088)	(0.081)	(0.082)
Rural area	-0.248**	-0.215*	-0.191	-0.170
	(0.112)	(0.119)	(0.117)	(0.113)
Firm age	0.000	0.001	0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.002)
Owner age 26-41	-0.251	-0.216	-0.321	-0.230
	(0.227)	(0.230)	(0.207)	(0.203)
Owner age 42-57	-0.263	-0.236	-0.356*	-0.262
	(0.229)	(0.232)	(0.205)	(0.206)
Owner age 58-76	-0.311	-0.303	-0.478**	-0.403**
	(0.225)	(0.232)	(0.199)	(0.193)
Owner age 77-	-0.313	-0.279	-0.510**	-0.465**
	(0.243)	(0.248)	(0.223)	(0.217)
Female owner	0.304***	0.273***	0.253***	0.269***
	(0.064)	(0.058)	(0.051)	(0.051)
Owner: High school	0.167***	0.101**	0.100**	0.100**
	(0.042)	(0.039)	(0.040)	(0.040)
Owner: Vocational school	-0.046	-0.159	-0.216*	-0.263*
	(0.127)	(0.117)	(0.121)	(0.131)
Owner: University	0.315***	0.208***	0.167**	0.161**
	(0.051)	(0.053)	(0.069)	(0.065)
Owner: Graduate degree	0.205**	0.084	0.047	0.039
	(0.095)	(0.102)	(0.119)	(0.109)
Multinational linkages:				
MNF customer linkage		0.415***	0.356***	0.349***
		(0.036)	(0.038)	(0.039)
MNF supplier linkage		0.222***	0.201***	0.201***
		(0.042)	(0.044)	(0.043)
Support exposure:				
Public support receipt			0.427***	0.405***
			(0.097)	(0.102)
Private support receipt			0.272***	0.259***
			(0.062)	(0.060)
Peer environment:				
Peer MNF linkage prevalence				-0.184
				(0.407)
Peer public support prevalence				1.606*
				(0.829)
Peer private support prevalence				0.622*
				(0.358)
Peer digital adoption prevalence				-1.023
				(1.089)
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
N	2864	2864	2864	2864
R-squared	0.310	0.362	0.380	0.390

Note: * p<0.10, ** p<0.05, *** p<0.01. The dependent variable is a standardized measure of digital adoption depth, based on the share of employees engaged in digital-related tasks. The original categorical variable is transformed into an ordinal measure and standardized to have mean zero and unit variance. Coefficients therefore represent differences in digital depth measured in standard deviations. Peer prevalence variables are constructed as leave-one-out shares of other firms in the same region-industry cell exhibiting the corresponding characteristic. The omitted owner education category is middle school or less, and the omitted owner age category is 18-25. Standard errors (in parentheses) are clustered at the region level.

Source: Authors' calculations.

Table 7. Determinants of Implementation Effectiveness

Dependent variable: Implementation effectiveness

	(1) Baseline	(2) +MNF	(3) + Support	(4) +Peer
Firm characteristics:				
Log employees	0.064**	0.056**	0.053**	0.044*
	(0.026)	(0.024)	(0.023)	(0.023)
Post-2020 entrant	-0.650***	-0.591***	-0.579***	-0.585***
	(0.068)	(0.072)	(0.073)	(0.073)
Rural area	-0.128**	-0.110*	-0.101*	-0.107*
	(0.060)	(0.060)	(0.059)	(0.059)
Firm age	-0.002	-0.002	-0.002	-0.002
	(0.003)	(0.002)	(0.002)	(0.002)
Owner age 26-41	1.441***	1.458***	1.408***	1.452***
	(0.170)	(0.172)	(0.173)	(0.169)
Owner age 42-57	1.377***	1.390***	1.331***	1.372***
	(0.157)	(0.161)	(0.160)	(0.157)
Owner age 58-76	1.226***	1.228***	1.149***	1.195***
	(0.157)	(0.160)	(0.165)	(0.162)
Owner age 77-	1.093***	1.108***	1.003***	1.037***
	(0.228)	(0.220)	(0.227)	(0.219)
Female owner	0.294***	0.277***	0.267***	0.261***
	(0.067)	(0.066)	(0.067)	(0.067)
Owner: High school	-0.042	-0.079	-0.080	-0.074
	(0.076)	(0.078)	(0.078)	(0.080)
Owner: Vocational school	-0.380***	-0.446***	-0.479***	-0.481***
	(0.111)	(0.110)	(0.112)	(0.116)
Owner: University	-0.327***	-0.388***	-0.407***	-0.404***
	(0.082)	(0.085)	(0.088)	(0.090)
Owner: Graduate degree	-0.363***	-0.431***	-0.448***	-0.434***
	(0.099)	(0.103)	(0.103)	(0.108)
Multinational linkages:				
MNF customer linkage		0.236***	0.208***	0.212***
		(0.043)	(0.042)	(0.043)
MNF supplier linkage		0.117***	0.110**	0.112**
		(0.041)	(0.040)	(0.041)
Support exposure:				
Public support receipt			0.258***	0.267***
			(0.076)	(0.077)
Private support receipt			0.102***	0.097**
			(0.035)	(0.036)
Peer environment:				
Peer MNF linkage prevalence				0.597**
				(0.277)
Peer public support prevalence				0.566
				(0.481)
Peer private support prevalence				-0.349
				(0.261)
Peer digital adoption prevalence				0.472
				(0.772)
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
N	2864	2864	2864	2864
R-squared	0.133	0.150	0.154	0.157

Note: * p<0.10, ** p<0.05, *** p<0.01. The dependent variable is a standardized measure of self-reported implementation effectiveness, based on firms' self-reported assessment of digital tool implementation outcomes. The variable is standardized to have mean zero and unit variance. Coefficients therefore represent differences in implementation effectiveness measured in standard deviations. Peer prevalence variables are constructed as leave-one-out shares of other firms in the same region-industry cell exhibiting the corresponding characteristic. The omitted owner education category is middle school or less, and the omitted owner age category is 18-25. Standard errors (in parentheses) are clustered at the region level.

Source: Authors' calculations.

Table 8. Lewbel IV Robustness: Digital Adoption and Implementation Effectiveness

	(1) Breadth	(2) Breadth	(3) Breadth	(4) Breadth	(5) Depth	(6) Depth	(7) Depth	(8) Depth	(9) IE	(10) IE	(11) IE	(12) IE
MNF customer linkage	0.256^{*}				0.619^{***}				0.964^{***}			
	(0.135)				(0.188)				(0.159)			
MNF supplier linkage		0.473^{**}				0.476^{**}				0.352		
		(0.222)				(0.188)				(0.241)		
Public support receipt			0.036				0.609^{***}				0.747^{***}	
			(0.176)				(0.136)				(0.096)	
Private support receipt				0.341^{*}				0.321^{***}				0.372^{**}
				(0.176)				(0.107)				(0.177)
Firm characteristics control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2864	2864	2864	2864	2864	2864	2864	2864	2864	2864	2864	2864
KP LM	15.403	14.224	11.583	15.945	15.403	14.224	11.583	15.945	15.403	14.224	11.583	15.945
KP LM p-value	0.052	0.076	0.171	0.043	0.052	0.076	0.171	0.043	0.052	0.076	0.171	0.043
KP Wald F	11.958	4.145	87.755	7.942	11.958	4.145	87.755	7.942	11.958	4.145	87.755	7.942
Hansen J	10.761	11.860	7.401	11.170	6.024	14.005	9.851	9.834	13.178	11.959	9.389	13.960
Hansen J p-value	0.149	0.105	0.388	0.131	0.537	0.051	0.197	0.198	0.068	0.102	0.226	0.052

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports instrumental variable estimates using the heteroskedasticity-based identification strategy proposed by Lewbel (2012). Endogenous regressors are instrumented using internally generated instruments constructed from the model's exogenous variables. Breadth refers to the standardized digital adoption index based on tool adoption. Depth refers to the standardized share of employees engaged in digital-related tasks. IE refers to standardized self-reported implementation effectiveness. Coefficients are interpreted as changes in the dependent variable measured in standard deviations. The Kleibergen-Paap (KP) LM statistic and its p-value test for underidentification, while the KP Wald F-statistic reports the strength of the generated instruments under heteroskedasticity. The Hansen J statistic tests the validity of overidentifying restrictions. Standard errors are clustered at the regional level.
Source: Authors' calculations.

Table 9. Digital Adoption Breadth and Firm Performance Resilience

Dependent variable: Resilient sales performance (2022 ≥ 2019)

	(1) Baseline	(2) +MNF	(3) +Support	(4) +Peer
Digital adoption breadth	0.045*	0.027	0.035	0.043**
	(0.024)	(0.027)	(0.022)	(0.019)
Multinational linkages:				
MNF customer linkage		0.068**	0.031	0.023
		(0.029)	(0.030)	(0.031)
MNF supplier linkage		0.036*	0.013	0.010
		(0.020)	(0.023)	(0.023)
Support exposure:				
Public support receipt			0.227***	0.219***
			(0.042)	(0.034)
Private support receipt			0.177***	0.166***
			(0.030)	(0.029)
Peer environment:				
Peer MNF linkage prevalence				0.068
				(0.194)
Peer public support prevalence				1.220***
				(0.205)
Peer private support prevalence				0.248
				(0.155)
Peer digital adoption prevalence				-1.044***
				(0.255)
Firm characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
N	2014	2014	2014	2014
R-squared	0.320	0.326	0.359	0.390

Note: * p<0.10, ** p<0.05, *** p<0.01. The dependent variable is an indicator equal to one if the firm's performance in 2022 is non-negative relative to 2019 (resilience outcome). The main explanatory variable, digital adoption breadth, is a standardized index constructed by standardizing each digital tool indicator across firms, summing within firm, and standardizing the sum to have mean zero and unit variance. Coefficients therefore represent the change in the probability of resilience associated with a one-standard-deviation difference in digital adoption breadth. Peer prevalence variables are leave-one-out shares of other firms in the same region-industry cell exhibiting the corresponding characteristic. The omitted owner education category is middle school or less, and the omitted owner age category is 18-25. Standard errors are clustered at the region level.

Source: Authors' calculations.

Table 10: Digital Adoption Breadth and Firm Performance Resilience by Tool Category

Dependent variable: Resilient sales performance (2022 ≥ 2019)

	(1) FC	(2) PR	(3) LG	(4) SM	(5) OI	(6) AT
Adoption breadth (category-specific)	-0.075***	0.024*	-0.041***	0.119***	0.077***	0.030**
	(0.016)	(0.013)	(0.009)	(0.011)	(0.010)	(0.012)
Multinational linkages						
MNF customer linkage	0.059**	0.035	0.050*	-0.015	0.023	0.033
	(0.028)	(0.030)	(0.028)	(0.032)	(0.030)	(0.029)
MNF supplier linkage	0.063***	0.025	0.047**	0.001	0.004	0.024
	(0.021)	(0.027)	(0.022)	(0.026)	(0.027)	(0.027)
Support exposure						
Public support receipt	0.164***	0.220***	0.209***	0.180***	0.213***	0.210***
	(0.037)	(0.036)	(0.037)	(0.036)	(0.034)	(0.033)
Private support receipt	0.120***	0.169***	0.146***	0.141***	0.140***	0.159***
	(0.033)	(0.030)	(0.030)	(0.027)	(0.025)	(0.029)
Peer environment						
Peer MNF linkage prevalence	0.054	0.064	0.064	0.088	0.064	0.062
	(0.185)	(0.197)	(0.192)	(0.182)	(0.190)	(0.195)
Peer public support prevalence	1.069***	1.211***	1.189***	1.032***	1.204***	1.221***
	(0.209)	(0.206)	(0.200)	(0.210)	(0.204)	(0.196)
Peer private support prevalence	0.194	0.248	0.269*	0.243	0.238	0.246
	(0.140)	(0.152)	(0.140)	(0.148)	(0.146)	(0.149)
Peer digital adoption prevalence	-0.772**	-0.987***	-0.869***	-0.949***	-1.106***	-0.980***
	(0.299)	(0.262)	(0.297)	(0.250)	(0.245)	(0.264)
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2014	2014	2014	2014	2014	2014
R-squared	0.401	0.387	0.393	0.423	0.405	0.388

Note: * p<0.10, ** p<0.05, *** p<0.01. The dependent variable equals one if firm sales in 2022 are non-negative relative to 2019. Each column uses a standardized adoption index for a specific digital tool category (FC: foundational communication and computing; PR: procurement; LG: logistics; SM: sales management; OI: operational infrastructure; AT: advanced tools). Each index is constructed by standardizing individual tool indicators across firms and aggregating them to have mean zero and unit variance; coefficients therefore represent percentage-point changes in the probability of resilience associated with a one-standard-deviation difference in adoption breadth. Peer prevalence variables are leave-one-out shares of other firms in the same region-industry cell exhibiting the corresponding characteristic. Support variables indicate whether the firm has ever received assistance and do not capture timing. The omitted owner education category is middle school or less and the omitted owner age category is 18-25. Standard errors (in parentheses) are clustered at the region level.
Source: Authors' calculations.

Table 11. Digital Adoption Depth and Firm Performance Resilience

Dependent variable: Resilient sales performance (2022 ≥ 2019)

	(1) Baseline	(2) +MNF	(3) +Support	(4) +Peer
Adoption depth (digital workforce share)	0.124***	0.116***	0.104***	0.091***
	(0.022)	(0.023)	(0.021)	(0.021)
Multinational linkages				
MNF customer linkage		0.034	0.011	0.012
		(0.028)	(0.029)	(0.029)
MNF supplier linkage		0.023	0.008	0.012
		(0.028)	(0.029)	(0.027)
Support exposure				
Public support receipt			0.183***	0.180***
			(0.044)	(0.036)
Private support receipt			0.154***	0.146***
			(0.023)	(0.024)
Peer environment				
Peer MNF linkage prevalence				0.115
				(0.188)
Peer public support prevalence				1.031***
				(0.220)
Peer private support prevalence				0.193
				(0.149)
Peer digital adoption prevalence				-0.907***
				(0.292)
Firm characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
N	2014	2014	2014	2014
R-squared	0.359	0.361	0.384	0.407

Note: * p<0.10, ** p<0.05, *** p<0.01. The dependent variable is an indicator equal to one if the firm's performance in 2022 is non-negative relative to 2019 (resilience outcome). The main explanatory variable, digital adoption depth, is a standardized measure based on the share of employees engaged in digital-related tasks. Coefficients therefore represent the change in the probability of resilience associated with a one-standard-deviation difference in digital adoption depth. Peer prevalence variables are leave-one-out shares of other firms in the same region-industry cell exhibiting the corresponding characteristic. The omitted owner education category is middle school or less, and the omitted owner age category is 18-25. Standard errors are clustered at the region level.

Source: Authors' calculations.

Table 12. Lewbel IV Robustness: Digital Adoption and Firm Performance Resilience

Dependent variable: Resilient sales performance (2022 ≥ 2019)

	(1) Breadth: ALL	(2) Breadth: FC	(3) Breadth: PR	(4) Breadth: LG	(5) Breadth: SM	(6) Breadth: OI	(7) Breadth: AT	(8) Depth
Digital adoption index	0.108^{*}	-0.054	-0.076	-0.019	0.203^{***}	0.161^{***}	0.061^{***}	0.233^{***}
	(0.061)	(0.087)	(0.056)	(0.039)	(0.038)	(0.031)	(0.019)	(0.041)
Firm characteristics control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2014	2014	2014	2014	2014	2014	2014	2014
KP LM	13.017	4.652	9.483	13.551	11.192	10.005	11.156	12.605
KP LM p-value	0.072	0.702	0.220	0.060	0.130	0.188	0.132	0.082
KP Wald F	5.069	3.127	12.052	20.364	10.347	10.874	36.420	28.190
Hansen J	10.121	11.356	11.837	7.704	9.900	8.818	6.769	9.488
Hansen J p-value	0.120	0.078	0.066	0.261	0.129	0.184	0.343	0.148

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports instrumental variable estimates using the heteroskedasticity-based identification strategy proposed by Lewbel (2012). Digital adoption variables are treated as endogenous and instrumented using internally generated instruments constructed from the model's exogenous covariates. Breadth: ALL refers to the overall standardized digital adoption breadth index constructed from all digital tools, while the remaining Breadth variables refer to standardized digital adoption indices for specific functional categories. Depth refers to the standardized share of employees engaged in digital-related tasks. The dependent variable is an indicator for resilient firm performance during the COVID-19 period. Since the digital adoption breadth measures are standardized, coefficients can be interpreted approximately as the change in the probability of resilience associated with a one-standard-deviation increase in digital adoption breadth. The Kleibergen-Paap (KP) LM statistic and its p-value test for underidentification, while the KP Wald F-statistic reports the strength of the generated instruments under heteroskedasticity. The Hansen J statistic tests the validity of overidentifying restrictions. Standard errors are clustered at the regional level.

Appendix A. Conceptual Framework

This appendix outlines the conceptual framework underlying the empirical analysis. The study addresses two related questions: (i) why some MSMEs exhibit higher digital adoption than others, and (ii) whether digital adoption enhances firm resilience during the COVID-19 shock. Accordingly, the empirical analysis distinguishes between an adoption dimension, which examines the determinants of digital adoption, and a performance dimension, which evaluates its economic consequences.

The framework is grounded in the technology diffusion literature synthesized by Paul Stoneman and Cristina Battisti (2010), which identifies three main mechanisms shaping the diffusion of new technologies: the rank model, the information diffusion (epidemic) model, and the stock model. These models provide a unified perspective on firm heterogeneity, learning dynamics, and competitive interactions.

Rank Model: Heterogeneity in Adoption Incentives

The rank model emphasizes persistent firm heterogeneity in expected returns to adoption across firms. Let the net return for firm i at time t be

$$\pi_i(t) = v_i(t) - p(t)(r + \delta),$$

where $v_i(t)$ denotes the expected operating benefit from a new technology adoption and $p(t)(r + \delta)$ represents the annualized capital cost of the technology, determined by the purchase price $p(t)$, the interest rate r, and the depreciation rate δ. Firms adopt when

$$\pi_i(t) \geq 0.$$

Because $v_i(t)$ varies across firms due to differences in managerial quality, organizational capacity, and external linkages, firms with higher expected returns adopt earlier. This heterogeneity in returns generate systematic variation in digital adoption across firms.

Information Diffusion (Epidemic) Model: Learning from Peers

The information diffusion model highlights informational spillovers in the diffusion process. Let $A(t) \in [0, 1]$ denote the share of firms that have already adopted the technology at time t. In epidemic diffusion models, the hazard of adoption for a non-adopting firm i at time t is proportional to the prevalence of prior adopters:

$$\lambda_i(t) = \beta A(t), \quad \beta > 0.$$

As more firms adopt, information about the technology spreads and uncertainty declines, increasing the probability of adoption among non-adopters. Aggregate diffusion depends both on the probability of adoption and on the remaining pool of non-adopters. The evolution of diffusion can therefore be written as

$$\dot{A}(t) = \beta A(t)\big(1 - A(t)\big),$$

which produces the well-known S-shaped diffusion path (Griliches, 1957). Firms operating in environments with higher adoption shares thus face stronger informational spillovers that may increase the likelihood of adoption.

Stock Model: Competitive Effects and Diminishing Returns

The stock model emphasizes competitive interactions among adopters. Let $N(t)$ denote the number of adopters at time t. The payoff from adoption can be written as

$$\pi_i(t) = v_i(t) - p(t)(r+\delta) - \gamma N(t), \quad \gamma > 0,$$

where the third term captures the erosion of profits as more firms adopt the technology. As adoption becomes widespread, the marginal benefits of adoption decline because competitive advantages diminish. A key implication is the presence of order effects: early adopters may capture larger benefits, while later adopters face lower incremental gains. This mechanism suggests that the economic value of digitalization depends not only on firm-level adoption but also on the surrounding diffusion environment.

Implications for Empirical Analysis

Taken together, these diffusion mechanisms explain both the determinants of adoption and the potential consequences of adoption in different environments. The rank model highlights firm-level heterogeneity in adoption incentives, while the information diffusion and stock models emphasize the role of the surrounding adoption environment through informational spillovers and competitive interactions.

In the empirical analysis, we include measures of the local peer environment to capture the broader diffusion and competitive context in which firms operate. These variables may reflect multiple underlying mechanisms, including informational spillovers and competitive pressures, which cannot be separately disentangled in our setting. Accordingly, they are treated as control variables that account for local conditions when estimating the association between firm-level characteristics—particularly multinational linkages and support exposure—and digital adoption.

Table A.1: Determinants of Digital Adoption Breadth by Tool Category

	(1) FC	(2) PR	(3) LG	(4) SM	(5) OI	(6) AT
Firm characteristics:						
Log employees	0.086**	0.072**	0.130***	0.063**	0.064**	0.082***
	(0.033)	(0.026)	(0.023)	(0.024)	(0.027)	(0.025)
Post-2020 entrant	0.158*	-0.029	0.360***	-0.735***	-0.489***	-0.369***
	(0.084)	(0.081)	(0.094)	(0.086)	(0.062)	(0.053)
Rural area	0.129*	0.077	0.057	-0.122	-0.197**	-0.081
	(0.066)	(0.076)	(0.074)	(0.073)	(0.084)	(0.069)
Firm age	0.006	0.005**	-0.002	0.005*	0.003	-0.001
	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Owner age 26-41	1.691***	1.540***	1.434***	0.633***	0.629***	0.171
	(0.155)	(0.270)	(0.262)	(0.182)	(0.146)	(0.127)
Owner age 42-57	1.651***	1.614***	1.397***	0.655***	0.595***	0.202
	(0.145)	(0.272)	(0.266)	(0.191)	(0.138)	(0.127)
Owner age 58-76	1.386***	1.306***	1.048***	0.529**	0.382**	0.089
	(0.179)	(0.327)	(0.290)	(0.219)	(0.183)	(0.173)
Owner age 77-	0.652***	0.653**	0.615*	0.276	0.083	-0.023
	(0.218)	(0.283)	(0.319)	(0.251)	(0.211)	(0.250)
Female owner	0.080	0.069	0.042	0.265***	0.285***	0.211**
	(0.078)	(0.060)	(0.058)	(0.043)	(0.041)	(0.077)
Owner: High school	0.289***	0.286***	0.149**	0.165***	0.223***	0.066
	(0.060)	(0.056)	(0.066)	(0.034)	(0.045)	(0.058)
Owner: Vocational school	0.650***	-0.068	0.016	-0.370***	-0.693***	-0.513***
	(0.127)	(0.184)	(0.124)	(0.077)	(0.086)	(0.097)
Owner: University	0.539***	0.367***	-0.025	0.214***	-0.125	-0.075
	(0.116)	(0.112)	(0.121)	(0.070)	(0.074)	(0.081)
Owner: Graduate degree	0.693***	0.434***	0.119	0.138*	-0.238***	-0.096
	(0.156)	(0.128)	(0.132)	(0.074)	(0.065)	(0.074)
Multinational linkages:						
MNF customer linkage	0.177**	0.319***	0.086	0.452***	0.256***	0.297***
	(0.072)	(0.063)	(0.095)	(0.056)	(0.042)	(0.067)
MNF supplier linkage	0.308***	0.223***	0.298**	0.230***	0.355***	0.244***
	(0.104)	(0.078)	(0.109)	(0.058)	(0.042)	(0.054)
Support exposure:						
Public support receipt	-0.652***	-0.250*	-0.129	0.345***	0.028	0.192
	(0.076)	(0.122)	(0.114)	(0.104)	(0.050)	(0.117)
Private support receipt	-0.535***	-0.244**	-0.445***	0.277***	0.336***	0.166**
	(0.061)	(0.092)	(0.038)	(0.065)	(0.108)	(0.072)
Peer environment:						
Peer MNF linkage prevalence	-0.037	0.078	0.004	0.059	0.180	0.193
	(0.280)	(0.228)	(0.325)	(0.263)	(0.238)	(0.160)
Peer public support prevalence	-2.021***	-0.545	-0.384	1.510***	-0.012	-0.563
	(0.671)	(0.625)	(0.434)	(0.511)	(0.365)	(0.471)
Peer private support prevalence	-0.649**	-0.610***	0.403	0.137	-0.024	-0.379
	(0.294)	(0.210)	(0.308)	(0.298)	(0.243)	(0.279)
Peer digital adoption prevalence	2.735**	0.740	1.724	0.201	1.481*	0.383
	(1.055)	(0.957)	(1.604)	(0.973)	(0.764)	(0.912)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2864	2864	2864	2864	2864	2864
R-squared	0.433	0.284	0.160	0.407	0.315	0.169

Note: * p<0.10, ** p<0.05, *** p<0.01. Each column uses a standardized index of adoption for the corresponding tool category (FC: fundamental communication and computing; PR: procurement; LG: logistics; SM: sales management; OC: overall company operations; AT: advanced tools). For each category, adoption indicators are standardized across firms and aggregated to have mean zero and unit variance; coefficients therefore represent differences in adoption breadth measured in standard deviations. Peer prevalence variables are constructed as leave-one-out shares of other firms in the same region-industry cell exhibiting the corresponding characteristic. The omitted owner education category is middle school or less, and the omitted owner age category is 18-25. Standard errors (in parentheses) are clustered at the region level.
Source: Authors.

Table A.2: Digital Adoption Breadth and Firm Performance Resilience (Using the Pre-pandemic Adoption Index)

Dependent variable: Resilient sales performance (2022 ≥ 2019)

	(1) Baseline	(2) +MNF	(3) +Support	(4) +Peer
Digital adoption breadth	0.045	0.024	0.033	0.044*
	(0.028)	(0.031)	(0.026)	(0.024)
Multinational linkages				
MNF customer linkage		0.070**	0.031	0.021
		(0.032)	(0.034)	(0.035)
MNF supplier linkage		0.042*	0.021	0.018
		(0.022)	(0.024)	(0.025)
Support exposure				
Public support receipt			0.215***	0.210***
			(0.044)	(0.036)
Private support receipt			0.165***	0.154***
			(0.033)	(0.033)
Peer environment				
Peer MNF linkage prevalence				0.074
				(0.165)
Peer public support prevalence				1.303***
				(0.223)
Peer private support prevalence				0.213
				(0.138)
Peer digital adoption prevalence				-0.885***
				(0.297)
Firm characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
N	1870	1870	1870	1870
R-squared	0.310	0.317	0.346	0.380

Note: * p<0.10, ** p<0.05, *** p<0.01. The dependent variable is an indicator equal to one if the firm's performance in 2022 is non-negative relative to 2019 (resilience outcome). The main explanatory variable, digital adoption breadth (ALL), is a standardized index constructed by standardizing each digital tool indicator across firms, summing within firm, and standardizing the sum to have mean zero and unit variance. Coefficients therefore represent the change in the probability of resilience associated with a one-standard-deviation difference in digital capability. Peer prevalence variables are leave-one-out shares of other firms in the same region-industry cell exhibiting the corresponding characteristic. Standard errors are clustered at the region level.

Source: Authors' calculations.

Table A.3: Digital Adoption Breadth and Firm Performance Resilience by Tool Category (Using the Pre-pandemic Adoption Index)

Dependent variable: Resilient sales performance (2022 ≥ 2019)

	(1) FC	(2) PR	(3) LG	(4) SM	(5) OI	(6) AT
Digital adoption breadth	-0.082***	0.023	-0.051***	0.122***	0.083***	0.030*
	(0.019)	(0.017)	(0.010)	(0.012)	(0.012)	(0.016)
Multinational linkages						
MNF customer linkage	0.057*	0.034	0.051	-0.017	0.017	0.031
	(0.031)	(0.034)	(0.031)	(0.036)	(0.033)	(0.033)
MNF supplier linkage	0.069***	0.031	0.053**	0.002	0.007	0.029
	(0.022)	(0.029)	(0.024)	(0.028)	(0.029)	(0.029)
Support exposure						
Public support receipt	0.152***	0.212***	0.197***	0.171***	0.204***	0.202***
	(0.039)	(0.038)	(0.038)	(0.036)	(0.035)	(0.034)
Private support receipt	0.104***	0.156***	0.130***	0.132***	0.127***	0.147***
	(0.036)	(0.034)	(0.033)	(0.029)	(0.027)	(0.031)
Peer environment						
Peer MNF linkage prevalence	0.065	0.076	0.070	0.110	0.066	0.066
	(0.161)	(0.166)	(0.165)	(0.152)	(0.162)	(0.168)
Peer public support prevalence	1.113***	1.283***	1.257***	1.131***	1.307***	1.298***
	(0.215)	(0.222)	(0.214)	(0.228)	(0.220)	(0.210)
Peer private support prevalence	0.145	0.208	0.233*	0.200	0.206	0.211
	(0.118)	(0.134)	(0.116)	(0.135)	(0.128)	(0.130)
Peer digital adoption prevalence	-0.707**	-0.860***	-0.723**	-0.800**	-0.891***	-0.846**
	(0.323)	(0.298)	(0.328)	(0.303)	(0.305)	(0.299)
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1870	1870	1870	1870	1870	1870
R-squared	0.393	0.377	0.385	0.413	0.396	0.379

Notes: * p<0.10, ** p<0.05, *** p<0.01. The dependent variable equals one if firm sales in 2022 are non-negative relative to 2019. Each column uses a standardized adoption index for a specific digital tool category (FC: foundational communication and computing; PR: procurement; LG: logistics; SM: sales management; OI: operational infrastructure; AT: advanced tools). Each index is constructed by standardizing individual tool indicators across firms and aggregating them to have mean zero and unit variance; coefficients therefore represent percentage-point changes in the probability of resilience associated with a one-standard-deviation difference in adoption breadth. Peer prevalence variables are leave-one-out shares of other firms in the same region-industry cell exhibiting the corresponding characteristic. Support variables indicate whether the firm has ever received assistance and do not capture timing. Standard errors (in parentheses) are clustered at the region level.
Source: Authors' calculations.