E-Commerce, Digital Literacy, and Rural Household Consumption in India

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Abstract: The size of e-commerce market in India has expanded rapidly over the last decade. We analyse the unit-level data from two waves of Household Consumption Expenditure Survey (HCES) conducted in 2022-23 and 2023-24 to quantify the welfare gains from e-commerce expansion in rural India. Specifically, we examine whether household who make online purchases have higher consumption expenditure and a more diversified consumption basket compared to those who do not make online purchases. Using the Lewbel (2012)'s identification strategy, which combines external instruments with heteroscedasticity-based instruments, we estimate that online purchasing significantly increase the monthly per capita expenditure (MPCE) of rural households by 18.5 percent. The magnitude of this consumption effect differs across the three components of the consumption basket, food, consumables, and durables, with the largest effect observed for durable goods. Further, the results on composition of consumption basket indicates that online purchasing led to reallocation of consumption expenditure towards consumables and durables, which were previously inaccessible for households in rural areas. Finally, we show that the ability to make digital transactions is a crucial mediating variable that has an offsetting impact on households without digital literacy.

Keywords: Online Purchase, Household Consumption, Digital Literacy

JEL Codes: L81, D12, and O33

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1. Introduction

As the penetration of information and communication technologies (ICTs) has accelerated in developing economies, e-commerce has gained popularity, becoming a significant driver of economic growth. In India, the e-commerce market has grown from USD 14 billion in 2014 to USD 125 billion in 2024[1], a ninefold increase driven by rising mobile phone ownership, increased internet connectivity, the spread of digital payment systems, and policy support for digital infrastructure. This expansion in e-commerce has the potential to change the consumption basket of households by making online purchases feasible. The digital platforms reduce information frictions, enable price comparisons, and expand the range of products beyond what is available locally (Liu et al., 2025). The impact is likely to be higher in the rural areas since the platforms connect rural consumers with sellers beyond the local market and expand consumption opportunities. However, whether this expansion translates into measurable welfare gains, reflected in higher consumption expenditure and a more diversified consumption basket remains an empirical question.

Research on expansion of ICT's has examined how the ease of information search and improved communication facilitated by these tools have affected various socio-economic outcomes. Mobile phone ownership has shown to increase female labour force participation (Jain, 2021; Jain & Chatterjee, 2024), reduce price dispersion and improve producer welfare in agricultural markets (Jensen, 2007) and strengthen household risk-sharing through remittance networks (Blumenstock et al., 2016; Jack & Suri, 2014). Similarly, internet use is linked with better learning outcomes for children (Derksen et al., 2022), higher mental well-being (Guan & and Tena, 2024) and formation of social capital (Bauernschuster et al., 2014). Beyond their role as information and communication tools, ICTs also function as service delivery platforms that directly shape household consumption decisions, particularly through digital payments and e-commerce platforms. Digital payments have been shown to influence consumer spending (Agarwal et al., 2024) and promote financial inclusion (Demirgüç-Kunt et al., 2021; Grzybowski et al., 2023). The evidence from China further documents that e-commerce platforms have generated substantial consumption effects including higher consumption growth (Luo et al., 2019), reduced inequality across regions and income groups (Fan et al., 2018; Wang et al., 2025), and a shift towards more diversified and higher-quality consumption baskets, especially among rural households (Chen & Li, 2025). However, comparable evidence from India, where a slew of policy interventions has led to an expansion in digital infrastructure, is scarce.

[1] https://www.statista.com/statistics/792047/india-e-commerce-market-size/

India provides an ideal context to undertake this line of analysis since the Government of India has sought to reduce digital divides and in particular the rural-urban divide. One major initiative is the development of India's digital payments infrastructure, the Unified Payments Interface (UPI), which enables zero-fee mobile transactions. This is now ranked as the world's largest real-time payment system. The second initiative is the rollout of the BharatNet project to extend internet access across rural India. Both the UPI and BharatNet, whose objective is to reduce the rural-urban digital divide, required substantial public investments. Riding on the back of these public investments, by 2024, e-commerce not only steadily grew in India, but online delivery was available to all the postal codes or pincodes in India. There is substantial scope for further expansion once a larger proportion of internet users begin to shop online. While India has 850 million internet users, less than one in four shop online. This is in contrast to China and the United States of America where over 85 percent of users shop online (McKinsey & Company, 2025).

In this paper, we analyse unit-level data from the rural sample of India's nationally representative Household Consumption Expenditure Survey (HCES) conducted by India's National Statistics Office in 2022-23 and 2023-24. The HCES 2022-23 is the first survey with information on online purchases. We examine whether rural households that make online purchases have a diverse consumption basket and a higher level of consumption expenditure as compared to households that do not make online purchases.

The main empirical challenge is that online purchases are endogenous to consumption expenditure of households. It is plausible that households with certain preferences, ability, or other unobserved traits are more likely to engage in online purchasing and are ones with higher consumption levels. Also, households with higher consumption levels may systematically switch to online platforms for purchases. To account for these endogeneity concerns, we employ Lewbel (2012) heteroscedasticity based identification approach, wherein we combine external instruments with heteroscedasticity-based instruments to provide more robust estimates. We use two external instruments, district-level cell tower density and the ratio of rural households with mobile phone ownership in a district for our analysis. These variables capture the spatial differences in the digital readiness of districts facilitated by network infrastructure and mobile ownership. It is assumed that these district-level measures affect household consumption primarily through their influence on online purchasing behaviour.

After instrumenting online purchases with both external and heteroscedasticity-based instruments, we find that consumption expenditure of households that purchase online is 18.5 percent higher compared to households which do not make online purchases. The magnitude of this impact is

different for the three components of the consumption basket, viz. food, consumables and durables. Specifically, we find that the MPCE on food, consumables and durables is higher by 21 per cent, 25 per cent and 36 per cent, respectively. We also explore if online purchases alter the composition of consumption basket of households. The results indicates that online purchasing significantly increases the share of expenditure towards consumables and durable while there is no significant impact on share of food expenditure. These findings suggest that e-commerce has created new consumption opportunities for products that were previously inaccessible to rural households.

In order to highlight the mediating role of the ability of individuals to make digital payments, we analyse data from the Comprehensive Modular Survey (Telecom) conducted in 2025 and find that lack of knowledge on how to make online payments has an offsetting effect. This implies that beyond the provision of infrastructure it is equally important to address digital literacy in order to realise the welfare benefits of digital platforms.

This paper makes two important contributions to the existing literature. First, we advance the literature on ICTs and household consumption behavior by using online purchases as a direct indicator of ICT use, rather than the broad proxies commonly used in the literature. As ICT development has progressed from owning a mobile phone to internet use and more recently, utilisation of e-commerce services, several studies have examined the impact of ICT on the consumption decisions using different proxies of ICT. Using ownership of mobile phones as an indicator of ICT, Miyajima (2022) finds that ownership increases the consumption expenditure by 12-13 per cent in South Africa. Zhang et al. (2020) consider access to the internet as a proxy for ICT and document that internet availability within household premises reduces consumption inequality in Chinese counties with high internet penetration levels. The literature has also used digital finance as the indicator of ICT development and shows that the use of digital payments promotes household consumption, especially for recurring and subsistence goods, including food, clothing and transportation (Li et al., 2020; Yang et al., 2022). By focusing on online purchases, we are able to isolate the consumption effects of using digital platforms.

Second, while prior studies in the Indian context have examined the impact of ICTs on various outcomes such as female labour force participation (Jain & Chatterjee, 2024), female autonomy (Gupta et al., 2025) and firm performance (Y. Chen, 2026), we provide first empirical evidence on the effect of e-commerce on household consumption expenditure among rural households in

India. This is particularly important because nearly 65 per cent of India's population resides in rural areas and has huge potential to consumption growth.

The paper is structured as follows. In Section 2, we provide related literature and theoretical framework. Section 3 presents the data and descriptive statistics. Section 4 outlines the empirical strategy, and Section 5 presents the results. Section 6 concludes.

2. Related Literature and Theoretical Framework

E-commerce platforms have become an integral part of modern-day economies, supported by the penetration of ICTs. The macro-economic evidence suggests that the expansion of e-commerce is associated with sustained economic growth (Couture et al., 2021) and poverty alleviation (Lele & Goswami, 2017; Qin & Fang, 2022), while micro-level studies document the welfare benefits for households in rural economies, where traditional retail stores are limited (Chen & Li, 2025; Hjort & Poulsen, 2019; Xiao et al., 2025). The economic literature identifies three channels through which e-commerce can improve household welfare: the variety channel, price channel and transaction cost channel.

The first channel is the variety channel. Unlike physical stores, which can only stock products whose expected sales are sufficient to cover the fixed cost of shelf space, online platforms face a negligible cost of listing an additional product. The reduction in the fixed cost of entering the market allows e-commerce platforms to offer a wider range of products and services than any physical stores (Liu et al., 2025). This greater variety enhances consumer welfare, especially in rural areas where there are limited physical stores. The welfare gains from product variety are well-documented in the literature. Using the data on book sales from an online platform in the US, Brynjolfsson et al. (2003) document that the increased product variety led to consumer welfare gains of approximately 7-10 times larger than the gains from lower prices and increased competition. More recently, Brynjolfsson et al. (2025) decompose the estimates of demand elasticity into a two-element substitution framework and find that the gains from product variety were 40 times larger than the gains from lower prices in online book sales. In a similar vein, Fan et al. (2018) analyse the data from an online platform in China and show that e-commerce disproportionately increases welfare gains (expenditure shares) in small and remote cities by eliminating the negative impacts of distance on trade. Luo et al. (2019) find that the one standard

deviation change in e-commerce intensity (per capita share of online purchases) in a county is associated with a 0.303 increase in the growth in per capita household expenditure (log). They also find that this increase in per capita expenditure of households was more than twice as large for rural areas compared to urban ones, suggesting that the consumption impact of e-commerce is particularly pronounced in less developed regions where traditional retail access is limited.

The second channel through which online purchases impact the welfare is the price channel. It works through the increased price competition among the sellers. When consumers can compare prices across sellers, the competitive pressure increases, which restrains sellers from increasing prices above the competitive levels. Thus, e-commerce makes online purchases more price-effective for consumers. Using the partial equilibrium model with and without e- marketplaces, Choi & Suh (2005) establish that the e-marketplace improves the welfare gains for the consumers by reducing the search and information cost regarding the price comparability, details of the products and the reviews about the product quality. The empirical literature quantifies these gains for consumers. Using the data on individual purchases of insurance policies, Brown & Goolsbee (2002) show that a 10 percent increase in the share of individuals in a group using the internet reduces the average insurance prices for the group by 5 percent. In agricultural markets, Jensen (2007) finds that the use of mobile phones by Indian fishermen reduces the consumer prices by 4 percent and increases the consumer surplus by 6 percent.

Finally, the transaction cost channel captures welfare gains from saving the time and transportation costs of travelling to physical stores. Dolfen et al. (2023) quantify the gains from avoiding travel costs to local physical stores using the transaction-level data on credit and debit cards from 2007 to 2017 in the American markets. By accounting for the distance and the cost of travel to an offline store, they calculate the within-substitution gains and find that the welfare improvement from purchasing online amounts to 0.4 percent of total consumer spending in 2017. These gains rise to 1 percent of consumer spending, equivalent to more than $1000 per household per year when they account for both variety and transaction cost gains together. With regard to time savings associated with online purchases, Relihan (2022) studies the effects of the entry of online retailers in the US market on shopping trips of consumers using the daily credit and debit card transactions data. She finds that use of online platforms for shopping reduces the frequency of trips by 0.5 days per month (from 6.8 days per month to 6.3 days per month), a reduction of 7.4 percent.

While these three channels describe the potential welfare gains from e-commerce, the extent to which these gains are realised depends on the ability of households to make digital payments. Once households begin purchasing online, repeated interaction with digital platforms deepens their transactional capabilities through learning-by-doing, and reduces the friction for subsequent payments. The use of digital payments further reduces the transaction cost and processing times, leading to more frequent payments (Annan et al., 2024). Also, digital payments make individuals ignore their spending capacities because of the reduced psychological pain of spending in cash. These advantages of using digital payments, such as reduced costs, increased convenience, and broader accessibility have increased consumption opportunities and promoted market growth (Han et al., 2025; Li & Huang, 2025). The empirical evidence corroborates this mechanism. Using transaction-level data from the 2016 Indian demonetisation, Agarwal et al. (2024) provide causal evidence that the adoption of digital payments increases household spending. They also document a large consumption effect for temptation goods as compared to non-temptation goods[2]. Li et al. (2020) show that digital finance significantly promotes household consumption, especially for recurring items such as food, clothing, daily necessities, transportation, communication and entertainment. These findings suggest that the ability to make digital transactions may serve as a mediating channel between e-commerce and household consumption expenditure.

3. Data and Descriptive Statistics

We analyse unit-level data from two rounds of India's Household Consumption Expenditure Survey (HCES) conducted by the National Statistical Office (NSO) in 2022-23 and 2023-24. The survey follows a multi-stage stratified sampling design, wherein villages (in rural areas) and urban blocks (in urban areas) are the First Stage Units (FSUs), and households form the Ultimate Stage Units (USUs). Within each selected FSU, 18 households are drawn using simple random sampling without replacement.

In the 2022-23 round, from 8,723 rural and 6,115 urban FSUs, a total of 155,014 rural and 106,732 urban households were surveyed. Similarly, in the 2023-24 round, 154,357 rural and 107,596 urban households were surveyed out of 8,684 rural and 6,143 urban FSUs. Given that the survey design and the set of questionnaires remained identical across the two rounds, we pool the two cross-sections into a single dataset for analysis. Since the focus of our analysis is on rural household consumption expenditure, we restrict the pooled sample to rural areas with 306,818 households.

[2] They define temptation goods to include tobacco, carbonated drinks, sweets, and instant-prepared food.

The HCES collects information on household socioeconomic characteristics alongside itemised expenditure under three broad categories of consumption, viz. food, consumables and services, and durables. Information on the consumption of 405 items is available across both rounds. We aggregate the item-wise expenditure to calculate the monthly household consumption expenditure. From this, we arrive at the monthly per capita consumption expenditure (MPCE) by dividing the total monthly household expenditure by household size. We also calculate the MPCE for food, consumables and services and durables.

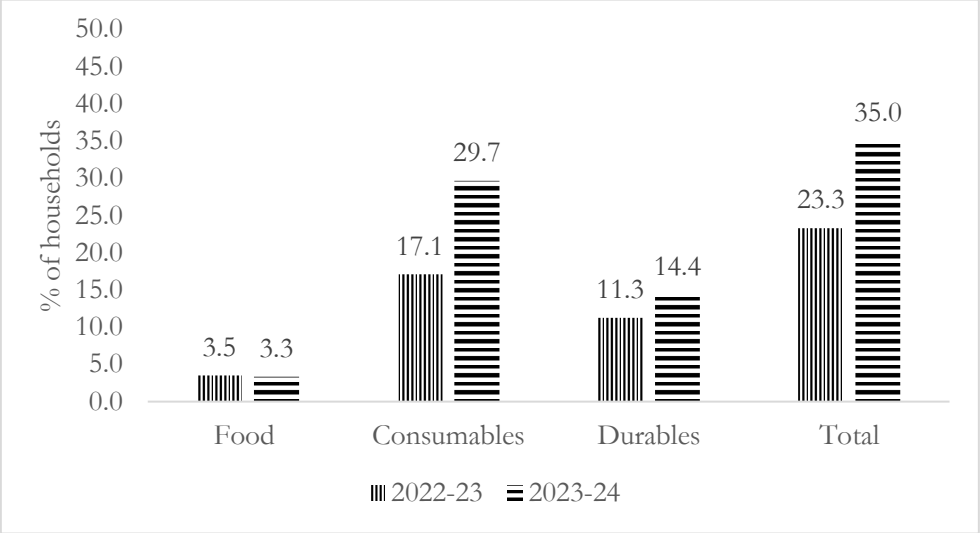
For the first time, as part of HCES 2022-23, India's National Statistics Office collected information on internet use and online purchases made by households. Similar to the information on total consumption expenditure, the survey also provides online expenditure of some selected goods and services under each of the three broad categories. We exploit this to define a binary indicator variable for online purchases that takes value one if a household reports any positive online expenditure in a given category, and zero otherwise. Internet use is also a binary indicator variable that takes value one if at least one member of the household has used the internet in past 30 days and zero otherwise.

Over the last decade, India's average rural MPCE increased by 40 percent (Government of India, 2024). This rise in consumption has been accompanied by a shift in the composition of the consumption basket. The share of food in the rural consumption basket declined from 52.9 percent in 2011-12 to 47 percent in 2023-24, with a steep fall in the share of cereals from 10.8 to 5 percent. The decline in the share of food in the consumption basket was mirrored by an increase in the share of expenditure on consumables and durables. In particular, the share of expenditure on consumables went up from 42.2 percent to 46.5 and the share of durables rose from 4.9 to 6.5 percent. The increase in overall consumption expenditure alongside the diversification of basket away from food to non-food items can be attributed to a variety of reasons including economic growth, rising incomes, change in preferences or increased digitisation which has opened new avenues for households to purchase from online marketplaces.

However, for this study, the expansion of e-commerce and its relationship with consumption expenditure of households is of particular interest since observed rise in rural consumption and the shift in its composition coincide with the rapid diffusion of internet access and digital platforms in rural India. From the survey data, we estimate that 23 per cent of rural households reported making online purchases in 2022–23, which rises sharply to 35 per cent in 2023–24 (Figure 1). This 12-percentage point increase within a year suggests that e-commerce is gaining traction in rural

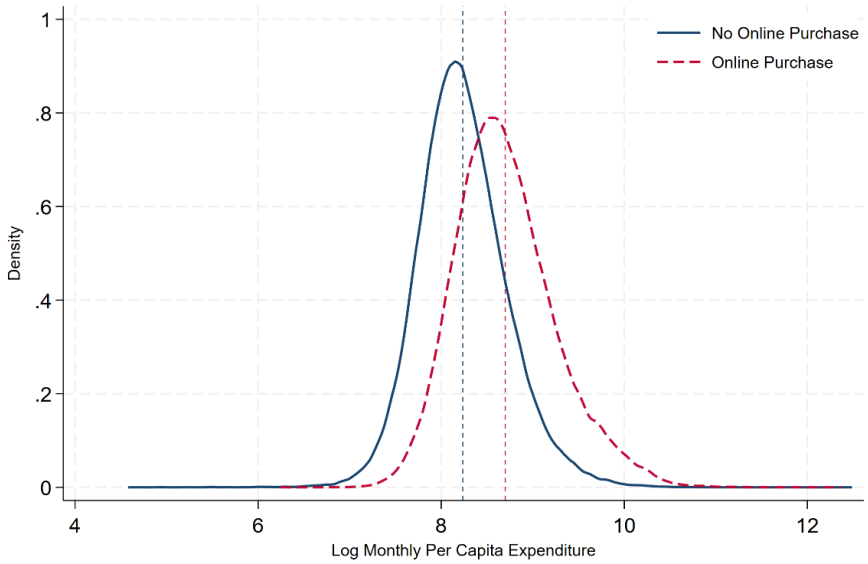
India. Next, we show how online purchases are related to consumption expenditure of households. Figure 2 presents the distribution of log MPCE separately for households who make online purchases and those who do not. The distribution reveals a clear pattern: households engaging in online purchasing exhibit higher consumption levels than those that do not. This is evident from the rightward shift in the consumption distribution of online purchasing households.

Figure 1: Proportion of rural household making online purchases across different consumption categories



Source: Author's calculation based on HCES 2022-23 and 2023-24

Figure 2: Online purchases and log monthly per capita consumption expenditure



Source: Author's calculation based on HCES 2022-23 and 2023-24

4. Empirical Model

4.1 Ordinary Least Squares

We estimate a model where the dependent variable Y_{hvds} is one of the following - logarithm of MPCE, logarithm of MPCE on food, consumables and services, and durables, and the share of expenditure in each of the three categories.

$$Y_{hvds} = \beta_0 + \beta_1 \, Online\ purchases_{hvds} + \beta_2 \, X_{hvds} + \gamma_{vds} + \varepsilon_{hvds} \qquad (1)$$

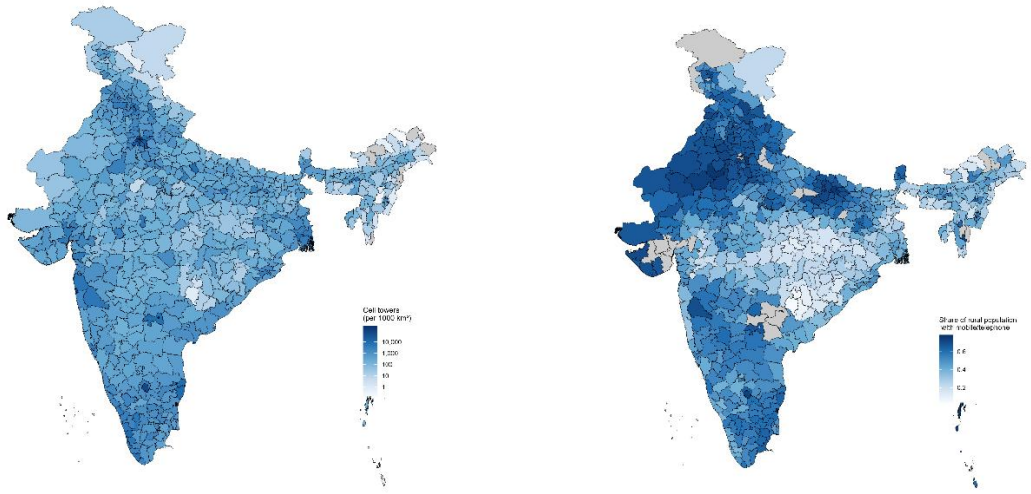
where h, v, d and s represent the household, village, district and state, respectively. Our main explanatory variable is a binary indicator variable that determines whether the household made online purchases or not. X_{hvds} is a vector of control for household characteristics. In line with the literature, we control for the gender, age, marital status, educational attainment and household size. Since we do not have information on the income of the household, we include the primary source of income of the household (self-employed, regular wage/salary, casual labour, others). Households classified as others have no labour income. We also include the social group (scheduled tribe, scheduled caste, other backward classes and others) and religion (Hindu, Islam, Christian and others) of the household as explanatory variables. In order to address geographical variations in digital tools, we include FSU fixed effects. We cluster the standard errors at the FSU level (villages in rural areas) to account for intra-cluster correlation. The summary statistics for variables is presented in the Appendix (Appendix Table 1).

4.2 Instrumental variable estimation

A major concern that arises from using OLS estimates is that it does not account for the potential endogeneity of households' online purchasing behaviour due to omitted variables and reverse causality. First, omitted variables may bias the results as unobserved factors such as consumer preferences, risk attitudes, and individual traits may simultaneously influence both the propensity to engage in online purchases and consumption expenditure. Second, there could be reverse causality, wherein consumption expenditure determines the likelihood of online purchasing, rather than the other way around. Households with greater purchasing power may be more inclined to adopt digital platforms due to convenience, wider product availability, and the ability to engage in price comparison shopping.

We tackle these endogeneity concerns by using the instrumental variable approach, where we instrument online purchases with two district-level variables, cell tower density and proportion of households with mobile phone ownership. Data on cell tower density is obtained from OpenCellID, an open-access and partially crowd-sourced repository of cellular infrastructure. This dataset provides the geographic coordinates (latitude and longitude) of Base Transceiver Stations (BTS). We match these BTS coordinates with Census districts using the district shapefile and construct cell tower density as the number of BTS per 1000 square kilometre in each district. To mitigate the influence of extreme values, we use the logarithm of cell tower density. Data for district level proportion of households with mobile ownership is drawn from Census 2011. Figure 3 maps the spatial pattern of cell tower density and proportion of rural households with mobile phone ownership across districts.

Figure 3: District-level map of cell tower density and mobile phone ownership



Source: OpenCellID and Census 2011

Our first instrument, cell tower density at the district level is guided by the work of Gupta et al. (2025) and Azam et al. (2024). It captures exogenous, supply-side variation in access to digital infrastructure at the district level. In India, where internet usage is predominantly mobile-based, a household's likelihood to engage in online purchasing depends on the availability of cellular infrastructure in its district. Households located in districts with a higher density of BTS face lower constraints in accessing mobile internet and are, therefore, more likely to participate in e-commerce. Thus, we expect cell tower density to be strongly correlated with households' online purchasing behaviour. At the same time, the spatial distribution of cell towers across districts has

largely been determined by the strategies of private tower companies operating within a regulated policy environment, rather than by household-level consumption demand. This institutional setting suggests that variation in tower density is plausibly exogenous to household consumption expenditure, thereby supporting the validity of the exclusion restriction.

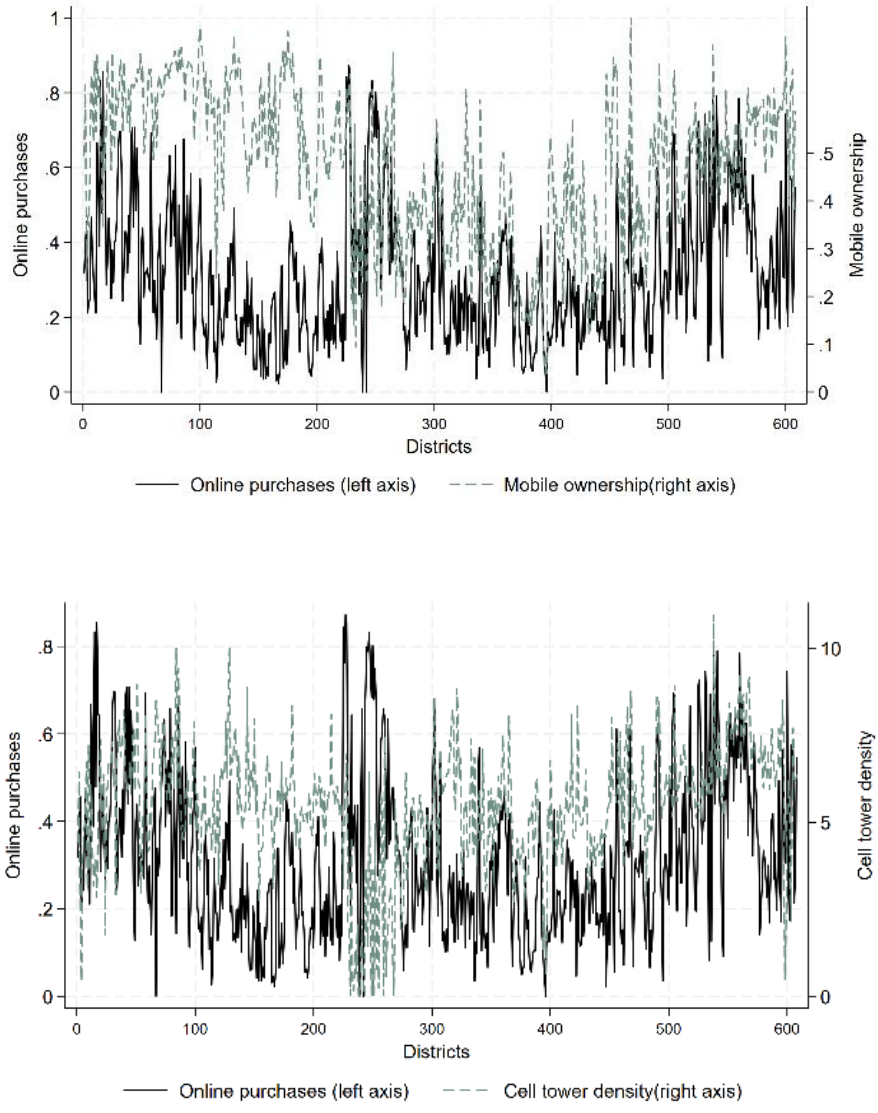
The second instrument, the proportion of rural households with mobile phone ownership in a district exploits the pre-existing variation in digital readiness that have made the expansion of e-commerce easier in certain districts than others. Districts where more households already owned mobile phones provide a more favourable environment for the adoption of online purchasing because of greater familiarity with mobile technology and stronger peer learning effects. Since we have used lagged mobile ownership at the district level, it cannot affect the current consumption decisions of households. This empirical strategy of using spatial differences in regional developmental indicators as a source of identification while identifying the impact of utilisation of digital services is well -established in the literature (Goldfarb & Prince, 2008; Han et al., 2025; Munyegera & Matsumoto, 2018; Zheng et al., 2019).

Together, the two instruments capture complementary dimensions of digital environment in a district, the physical availability of network infrastructure and the historical adoption of mobile technology and are expected to jointly predict household online purchasing behaviour at the first stage. However, there is one potential threat to our identification that IVs might be correlated with economic development indicators at the district-level, which could influence the mobile phone ownership and cell tower installation as well as the consumption expenditure. Therefore, we control for district-level characteristics such as the share of scheduled caste in district population, the share of scheduled tribe in district population, district literacy rate and share of cultivators in the workforce in our specification. These controls absorb the district-level heterogeneity in economic development that could confound the relationship between our instruments and the outcome variable. As a further robustness check, we include nighttime light intensity to account for unobserved economic activity at the district level (Appendix Table 2).

To ascertain the validity of the instruments, we check whether they satisfy the relevance and exclusion criteria. For relevance, we plot the district-level averages of online purchases against the cell tower density and the proportion of households with mobile phones. Figures 4 show that there exists a strong positive correlation between the district-level average of online purchases and the instruments. Next, to justify the exclusion restriction, that instruments influence the consumption expenditure of households only through the online purchases made by households, we employ a

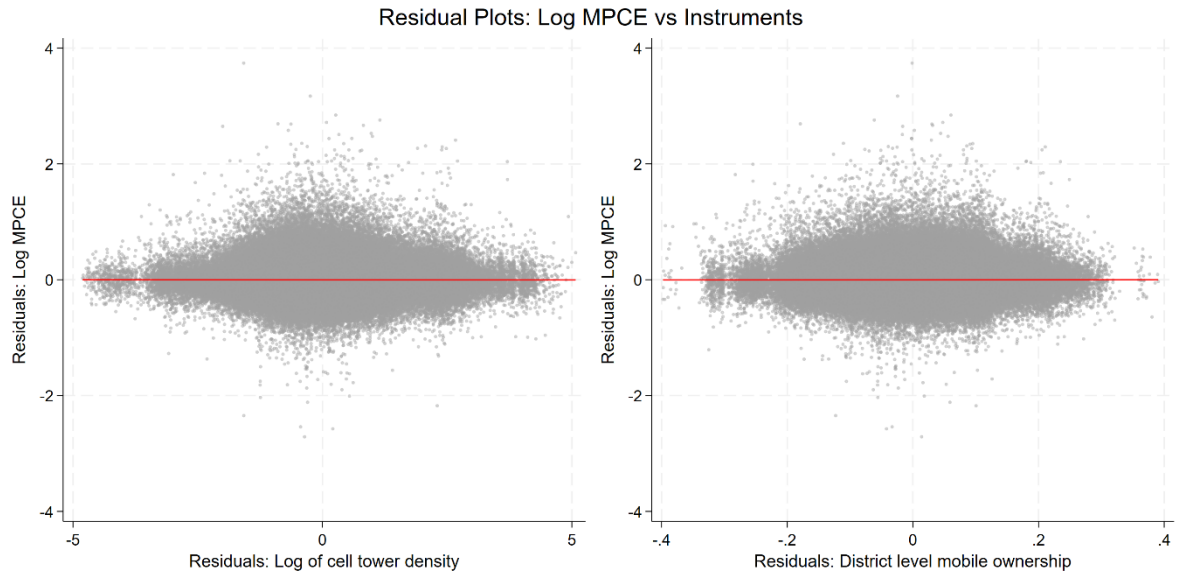
residual-based check. We obtain the residuals from two specifications, one by regressing consumption expenditure on online purchases and the other by regressing the instruments on online purchases. These two sets of residuals are then plotted against each other to assess if there remains any association between the instruments and consumption expenditure once the variation attributable to online purchases has been accounted for. Figures 5 show that there is no clear pattern or systematic correlation between two sets of residuals. This indicates the absence of any direct relationship between the instruments and consumption expenditure conditional on online purchases.

Figure 4: First stage correlation between average district level online purchases and district level IVs



Source: Author's calculation based on HCES 2022-23 and 2023-24

Figure 5: Residual plots: Log MPCE vs Instruments



Source: Author's calculation based on HCES 2022-23 and 2023-24

Further, to strengthen our identification strategy, we use the Lewbel (2012) approach, wherein we combine our external IVs with the heteroscedasticity-based instruments. The intuition behind this approach is that when the error term in the baseline model exhibits heteroscedasticity, one can exploit this feature to construct additional instruments internally, without requiring variables to satisfy the traditional exclusion restriction. Specifically, let S denote the vector of exogenous regressors in our baseline specification. The heteroscedasticity-based instruments are constructed as $[S - E(S)] \times \hat{\varepsilon}$, where $\hat{\varepsilon}$ are the residuals obtained by regressing online purchases on all exogenous variables. We verify for presence of heteroscedasticity in our model with the Breusch - Pagan test. The test rejects the null hypothesis of constant variance, suggesting the valid use of these statistical based instruments.[3] However, heteroskedasticity alone is not sufficient for identification. The validity of the generated instruments additionally requires that the variables used to construct them are orthogonal to the structural error term in the consumption equation. Another important point to note is that there is no accepted approach to select the vector S. It could be either be a subset of X or equal to X (all household controls). Considering these points, we follow the standard approach in existing studies and present results based on exogeneous household characteristics such as social group and religion. The combined use of external and heteroscedasticity-based instruments improves the efficiency of our 2SLS estimator and provides

[3] LM statistics = 1,135.17 and p value is 0.000

an additional layer of identification that is robust to concerns about the exclusion restriction of the external instruments or when the external instruments are weak. This methodology has been widely used in the literature (Bahl et al., 2022; Dang & Rogers, 2015; Grover & Sharma, 2026; Mishra & Smyth, 2015).

Our 2SLS specification is as follows:

$$Online\ purchases_{hvds} = \alpha_0 + \alpha_1\, Mobile_{ds} + \alpha_2\, Cell\ tower_{ds} + \alpha_3\, S_{hvds} + \alpha_4 X_{hvds} + (\delta_{ds} * t) + \gamma_s + \varepsilon_{hvds} \quad (2)$$

$$Y_{hvds} = \beta_0 + \beta_1 \widehat{Online\ purchases}_{hvds} + \beta_2\, X_{hvds} + (\delta_{ds} * t) + \gamma_s + \nu_{hvds} \quad (3)$$

Equations (2) and (3) represent the first and second stage regression, respectively. In the first stage, we obtain OLS estimates to predict the online purchases of households based on two external instruments, proportion of rural households with mobile phones in a district ($Mobile_{ds}$) and the log of cell tower density ($Cell\ tower_{ds}$) along with heteroscedasticity based instruments (S_{hvds}) [4] and other controls. δ_{ds} is a vector of control for district characteristics including the share of scheduled caste in district population, the share of scheduled tribe in district population, district literacy rate and share of cultivators in the workforce, interacted with the survey year t. Since our instruments are at the district level, we use state fixed effects (γ_s) in our model and cluster standard errors at the district level. In the second stage, we use the predicted values of online purchases to estimate their effect on household consumption expenditure.

4.3 Mediation effect model

To examine the mediation effect of digital literacy, we use the Comprehensive Modular Survey: Telecom (CMS-T) conducted by the National Statistical Office as part of the NSS 80th round during January to March 2025. Similar to HCES, the CMS-T follows a stratified multi-stage sampling design with villages as the first stage units and households as the ultimate stage units in rural areas, and collects comparable household socioeconomic characteristics. This consistency in survey design and variable definitions ensures that the mediation results are comparable to the main analysis, despite the smaller sample size (18,926 rural households). In addition to information

[4] We select exogenous household characteristics, specifically social group and religion, as the vector S for constructing the heteroscedasticity-based instruments, as these variables are predetermined and plausibly uncorrelated with unobserved determinants of consumption expenditure.

on online purchases and monthly per capita consumption expenditure of households, the survey also asks individual household members aged 15 and above whether they can perform online banking transactions on phones or computers. This information allows us to construct a measure of digital literacy at the household level. We consider a household to be digitally literate if at least one member of the household can perform digital transactions. We follow the framework of W. Chen & Li (2025) and estimate a two equation system :

$$DL_{hvds} = \beta_0 + \beta_1 \, Online\ purchases_{hvds} + \beta_2 \, X_{hvds} + (\delta_{ds} * t) + \gamma_s + \varepsilon_{hvds} \quad (4)$$

$$Y_{hvds} = \beta_0 + \beta_1 \, Online\ purchases_{hvds} + \beta_2 \, DL_{hvds} + \beta_3 \, X_{hvds} + (\delta_{ds} * t) + \gamma_s + \varepsilon_{hvds} \quad (5)$$

Here, DL_{hvds} is the mediating variable that denotes the digital literacy of households. X_{hvds} is a vector of control for household characteristics such as age of household head, gender of household head, caste, religion, household size and internet use. The meaning of all other variable is same as discussed above. Equation (4) examines the effect of online purchases on digital literacy, while equation (5) estimates the direct effect of online purchases on consumption outcomes after accounting for digital literacy of households. If the inclusion of digital literacy in the outcome equation (5) attenuates the coefficient on online purchases relative to the baseline specification, then we can say that a part of the effect of online purchases operates through digital literacy.

The main empirical challenge now is that both online purchases and digital literacy are endogenous. Like online purchases, the ability to make online transactions may be jointly determined with consumption outcomes due to unobserved factors such as ability, cognition, or motivation, resulting in biased and inconsistent estimates. Thus, to obtain consistent estimates, we instrument both the endogenous variables with external and internally generated instruments following Lewbel (2012). Our external instruments, district-level cell tower density and the share of rural households with mobile phone ownership, capture supply-side variation in access to digital infrastructure, as discussed in Section 4.2. These variables are relevant predictors of both endogenous variables but through different mechanisms. Cell tower density and mobile phone ownership affect online purchases by enabling access to e-commerce platforms, while they affect digital literacy by expanding opportunities for learning-by-doing through repeated interaction with digital devices and services. The use of infrastructure-based instruments for digital literacy is well established in the literature. Luo et al. (2021) instrument digital financial capability using internet

use, Choung et al. (2023) use participation in mobile network plan as an instrument for digital financial literacy and Li et al. (2025) exploit the regional telephone quantity and internet user count as a source of exogeneous variation for digital economy. We follow the same rationale and use the spatial differences in the availability of digital infrastructure for our identification.

5. Results

5.1 Baseline results

Table 1 reports the OLS and Lewbel IV estimates of the effects of online purchasing on the log of MPCE of rural households. Column (1) presents OLS estimates with FSU-level fixed effects and Column (2) presents 2SLS estimates where online purchases are instrumented using two external instruments, district-level cell tower density and district-level share of mobile ownership along with heteroscedasticity-based instruments following Lewbel (2012).

The OLS estimates show that there is positive and significant association between online purchases and consumption expenditure of households. Specifically, households that make online purchases record, on average, 12.6 percent higher MPCE compared to those that do not make online purchases. However, the estimates obtained through OLS may be biased because online purchases are endogenously determined with total consumption expenditure of households. Once we account for endogeneity by instrumenting online purchases with both external instruments and heteroscedasticity-based instruments, the coefficient of online purchases in Column (2) rises to 0.185, implying an 18.5 percent increase in MPCE. The upward revision in magnitude from OLS to IV arises because OLS estimates give the average treatment effect across all households, whereas the IV estimate identifies the local average treatment effect (LATE). The LATE is estimated only for the subpopulation of compliers, that is, households whose decision to purchase online is influenced by the availability of digital infrastructure, such as greater cell tower density and higher mobile phone ownership in their district (Angrist & Pischke, 2009). These households are likely to derive larger benefits from online purchasing because improved digital access enables them to overcome existing constraints in traditional retail markets, particularly limited product variety and restricted access to goods.

The first stage results of 2SLS estimates show that the instruments are highly correlated with the endogenous variable (Appendix Table 3). As expected, both the instruments are positively related to the online purchases indicating that greater access to digital infrastructure and higher mobile

penetration at the district level increase the likelihood of households engaging in online purchases. We also run a series of diagnostic tests, including under-identification, weak identification and F-test to support the validity of the 2SLS estimation. The Kleibergen-Paap rk LM statistic for under-identification rejects the null hypothesis that the model is under-identified. The test indicates that our excluded instruments are valid, that is, they are correlated with our endogenous regressor, online purchases. For weak identification, we find the Kleibergen-Paap rk Wald F-statistic to be greater than 10 across all our models. This rules out the problem of weak instruments in our model. Finally, the F-statistics are also reasonably high, indicating that our IVs have strong explanatory power.

Overall, we find that online purchasing raises the total MPCE of rural households. This is because e-commerce has created new consumption opportunities by reducing the information asymmetries and transaction cost which previously limited the consumption of households. The expansion to variety of products thus stimulates the latent consumption and drives an upward shift in MPCE. Similar results have been obtained in the broader literature, which emphasises the role of ICT in terms of mobile phone ownership, internet use, digital financial inclusion and e-commerce in stimulating the consumption expenditure of households (Agarwal et al., 2024; X. Luo et al., 2019; Miyajima, 2022; S. Zhang et al., 2020).

Household characteristics also determine the per capita consumption expenditure of rural households (Appendix Table 4). With regard to employment status, households with a major source of income from self-employment and regular wage-salaried jobs show a positive and significant correlation with consumption expenditure. This finding is consistent with human capital theory, which suggests that stable and higher-earning jobs generate higher disposable income, thereby enabling higher consumption levels. Self-employed and salaried households have more stable income streams compared to casual wage earners, resulting in higher consumption expenditure among self-employed and salaried households. The education level of the household head also has a positive correlation with the per capita consumption expenditure of households, as higher educational attainment is associated with increased earnings potential and better employment opportunities, which in turn support consumption expenditure. Household size negatively correlates with consumption expenditure, as higher the number of members in a household, lower is the per capita resource availability, given the total pool of resources at a point in time. These results are in line with the extant literature on household consumption (Miyajima, 2022; J. Zhang et al., 2022).

Table 1: Effect of online purchases on MPCE of rural households

	OLS	IV
Online purchases	0.126***	0.185***
	(0.002)	(0.021)
Household characteristics	Yes	Yes
District characteristics	No	Yes
FSU fixed effects	Yes	No
State fixed effects	No	Yes
Survey year fixed effects	Yes	Yes
Observations	306,804	306,818
F-statistic	1616.422	329.888
Kleibergen-Paap rk LM statistic		181.312
Kleibergen-Paap rk Wald F-statistic		32.457

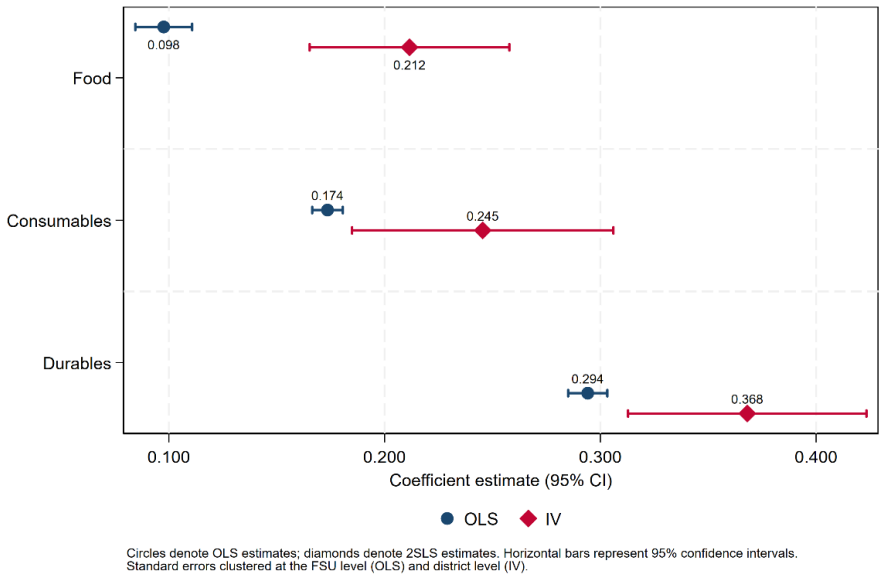
Notes: Column (1) presents Ordinary Least Squares (OLS) estimates with FSU-year fixed effects and survey year fixed effects. Column (2) presents Two-Stage Least Squares (2SLS) estimates using both external instruments (cell tower density and district-level share of mobile-only telephone ownership) and internally generated instruments following Lewbel (2012). The dependent variable is the log of MPCE. Household characteristics include age, gender, education of the household head, marital status, social group, religion, household size, occupation category of the household head, and internet access. District characteristics include time-interacted shares of SC population, ST population, literate population, and working population. Standard errors are clustered at the FSU level in Column (1) and at the district level in Column (2), reported in parentheses. The Kleibergen-Paap rk LM statistic tests the null hypothesis of under-identification. The Kleibergen-Paap rk Wald F-statistic for weak instruments. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

We next examine category-specific effects to identify which types of online purchases are associated with increase in household consumption expenditure. Specifically, we consider the effects of online purchases of food, consumables, and durable goods on MPCE of these respective categories. Figure 6 presents the OLS and IV estimates for category-specific effects while the regression tables are presented in the appendix (Appendix Table 5). The results show that online purchases significantly increase the MPCE across all three categories. In terms of magnitude of IV estimates, we find that the MPCE on food, consumables and durables is higher by 21 per cent, 25 per cent and 36 per cent, respectively. The effect is more pronounced for durable goods.

We further examine how online purchasing reshapes the composition of household consumption by estimating regressions with the share of total expenditure across major categories as the dependent variable (Figure 7 and Appendix Table 6). The results indicate that online purchasing leads to a reallocation of expenditure within the consumption basket, with a significant increase in the share devoted to consumables and durable goods. In contrast, we do not find any statistically significant effect on the share of food expenditure. This pattern can be understood in terms of differential constraints across consumption categories. Rural markets are often characterized by limited variety and quality, particularly for non-food items such as consumables and durables. The expansion of e-commerce alleviates these constraints by providing access to a wider range of

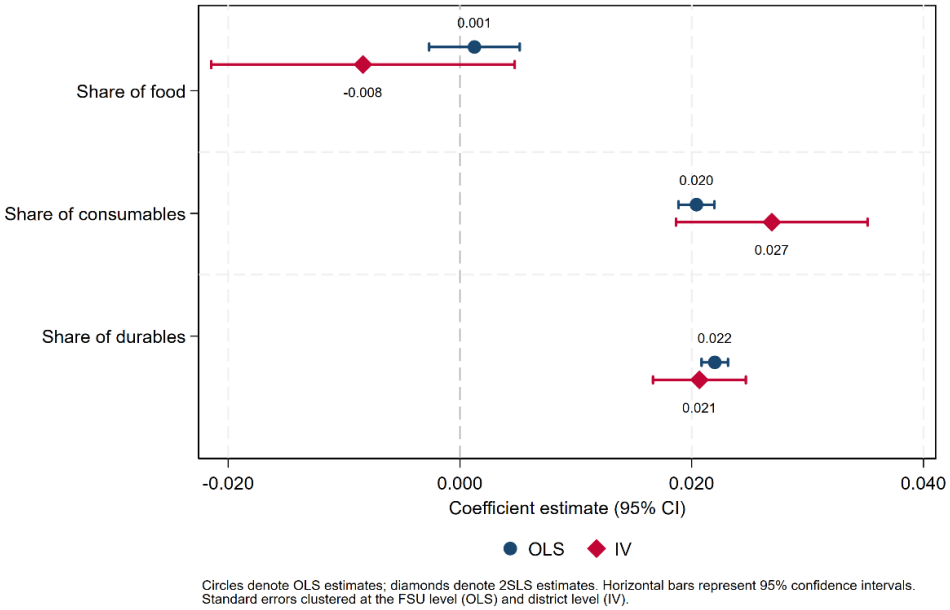
goods, along with doorstep delivery, which is especially relevant for bulky durable items. As a result, households shift a greater proportion of their expenditure towards these categories. On contrary, food items are more readily accessible through local markets. Online purchases for these items may only serve as a substitute for offline purchases and do not necessarily lead to higher consumption levels. Consequently, the share of food expenditure remains largely unchanged. These findings are in contrast with those of Li et al. (2020) as they find that households in China have positive effect on the proportion of recurring consumption expenditures, which indicates that digital market has more facilitating effects on the household expenditure for a basic livelihood.

Figure 6: Regression estimates of category-specific effects of online purchases on MPCE



Source: Author's calculation based on HCES 2022-23 and 2023-24

Figure 7: Regression estimates of effect of online purchases on composition of consumption expenditure



Source: Author's calculation based on HCES 2022-23 and 2023-24

5.2 Mediation effect

Table 2 presents the results for the mediation effects using the CMS-T data. We first verify that the baseline relationship between online purchases and consumption. Column (1) reports the baseline IV estimates that MPCE is 23 per cent higher for rural households who make online purchases compared to those who don't. The result is in sync with what we find with the HCES data. Column (2) verifies the first stage of mediation that online purchases are significantly related to the ability of households to make online transactions. This is explained by the learning-by-doing theory, that repeated interaction with digital platforms lowers informational and operational barriers to using technologies.

Column (3) includes digital literacy into the consumption equation. There are two noteworthy results. First, digital literacy has a positive and statistically significant effect on consumption expenditure, indicating that households with digital capabilities are better able to translate market access into actual consumption. Second, we find that online purchases have a significant impact on consumption expenditure even after controlling for the ability to make online transactions. In addition, we obtain a smaller coefficient for online purchases compared to the results obtained in

Column (1). This implies that a portion of the consumption-enhancing effect of online purchases operates through improvements in digital literacy.

The role of digital literacy operates most primarily through the use of online payment system. The ability to conduct online transactions reduces the time and effort costs associated with purchases, thereby encouraging instant purchases. Also, the use of digital payments reduces the psychological pain of spending and results in either more frequent purchases or increased spending. Conversely, the lack of skills to make digital payments creates a barrier that offsets the potential consumption benefits of online markets. The benefits of e-commerce are not solely driven by access to online marketplaces, but also depend on the household's ability to effectively transact within digital ecosystem. These findings are corroborated by studies on payment systems and consumption behaviour (Ahn & Nam, 2022; Greenacre & Akbar, 2019).

Table 2: Mediation effect (CMS-T)

	Log (MPCE)	Online payment	Log (MPCE)
	(1)	(2)	(3)
Online purchases	0.231***	0.189***	0.202***
	(0.069)	(0.014)	(0.062)
Online payment			0.189***
			(0.052)
Household characteristics	Yes	Yes	Yes
District characteristics	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Observations	18,926	18,926	18,926

Notes: The table reports the 2SLS estimates with both external and internally generated instruments. All specifications control for household characteristics, district characteristics and state fixed effects. Standard errors are clustered at district level (in parentheses). ***, **, * denote the significance at the 1%, 5% and 10% level, respectively.

5.3 Robustness checks

We conduct various robustness checks in this section to strengthen the confidence in our findings discussed in sections 5.1. These checks include the use of winsorized instrumental variables, falsification test and placebo test to assess the validity of instruments, use of alternate instruments and propensity score matching.

5.3.1 Winsorised instrumental variables

A potential concern with the baseline estimates is that the results may be sensitive to extreme values in our instrumental variables, cell tower density and the district-level share of mobile phone

ownership. Therefore, we winsorize both instruments at the 1st, 5th, and 10th percentiles of their respective distributions and obtain the 2SLS estimates under each threshold. We present the results in Table 3. Across all three specifications, the coefficient on online purchases remains positive and statistically significant at the 1 percent level. Moreover, the magnitude of the estimated effect of online purchasing on MPCE is consistent with the initial findings This stability in results indicates that the baseline estimates are not driven by outliers in the instruments.

Table 3: Robustness analysis: Winsorizing the extreme values of Ivs

	(1)	(2)	(3)
Online purchases	0.183***	0.177***	0.173***
	(0.021)	(0.020)	(0.020)
Household characteristics	Yes	Yes	Yes
District characteristics	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes
Observations	306,818	306,818	306,818

Notes: The table reports the 2SLS estimates with both external and internally generated instruments. Columns (1), (2) and (3) include the winsorized values of cell tower density and district-level share of mobile ownership at the 1%, 5% and 10% respectively. The dependent variable is the log of MPCE. All specifications control for household characteristics, district characteristics and state fixed effects. Standard errors are clustered at district level (in parentheses). ***, **, * denote the significance at the 1%, 5% and 10% level, respectively.

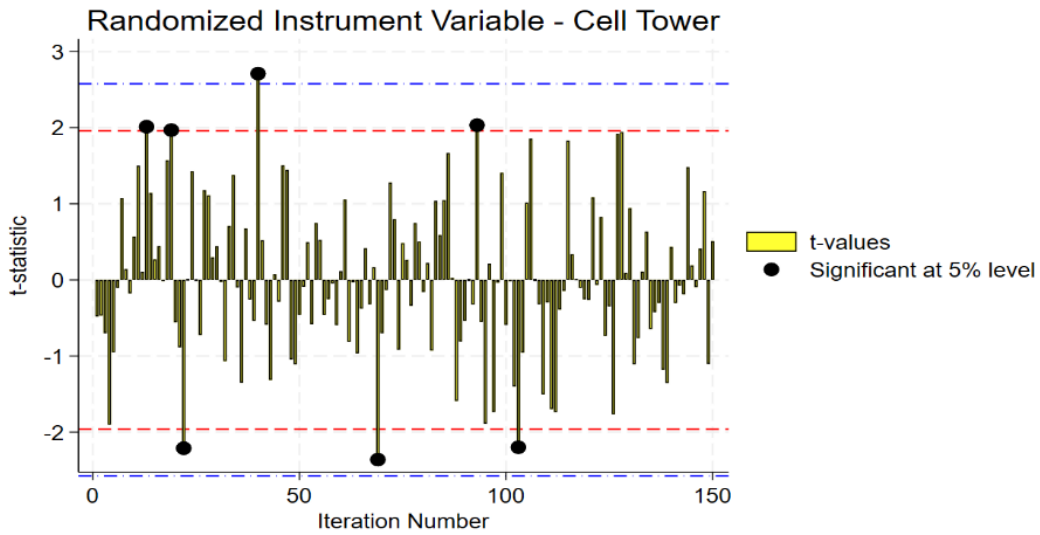
5.3.2 Falsification test: Relevance of IVs

As second check, we conduct Fisher randomisation test to assess the validity of the instruments. We randomly permute the values of two external instruments, district-level cell tower density and district-level mobile phone ownership share across districts and estimate the regression 150 times under each random assignment. If the instruments are valid, randomly assigning values to districts should break any meaningful relationship between the IVs and online purchases. Consequently, the resulting first stage t-statistics from the permuted regressions should centre around zero.

Figure 8A and 8B present the t-statistic distributions from the 150 permuted regressions for the cell tower density and mobile phone ownership, respectively. In both cases, the t-statistics are symmetrically distributed around zero with no directional pattern. For the cell tower density, approximately 95 percent of the iterations, that is, 143 out of 150 iterations do not yield a statistically significant first-stage relationship, and for mobile phone ownership, 94 percent of iterations show no significant association. We find that once the geographic structure of the instruments is removed through randomisation, the strong first-stage correlations observed in the baseline estimation disappear entirely for both instruments, confirming that they are driven by

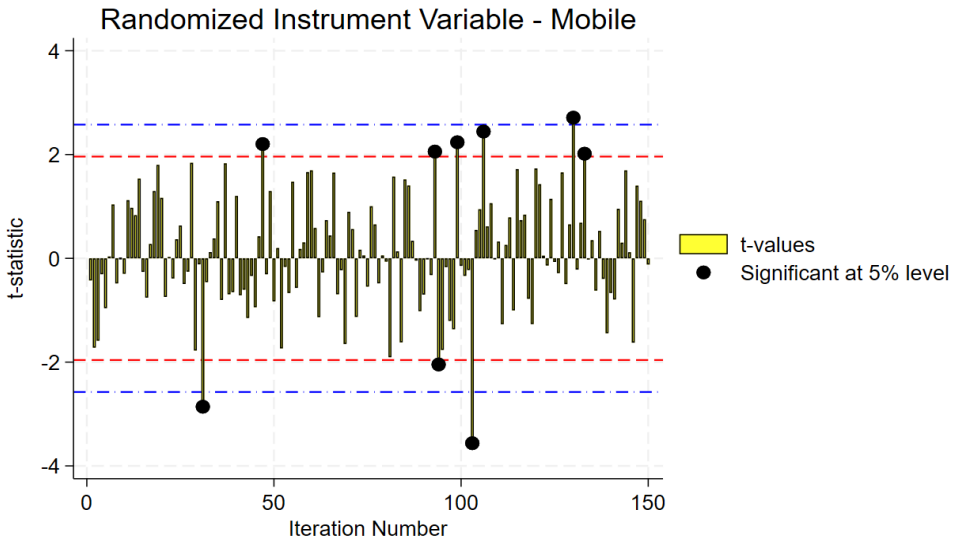
genuine spatial variation in digital infrastructure rather than spurious data features. These results rule out the possibility of spurious correlations and support the validity of our instrumental variable strategy.

Figure 8A: Falsification analysis: Validity of cell tower density



Source: Author's calculation based on HCES 2022-23 and 2023-2

Figure 8B: Falsification analysis: Validity of mobile phone ownership



Source: Author's calculation based on HCES 2022-23 and 2023-24

5.3.3 Placebo test: Exclusion restriction

The exclusion restriction for the validity of IVs requires that the instruments should affect the outcome only through the endogenous variable. While this assumption cannot be directly tested, we provide supporting evidence using a placebo test based on the HCES 2011–12, a period when e-commerce was virtually non-existent in rural India. We argue that if our instruments, cell tower density and district-level mobile ownership satisfy the exclusion restriction, they should have no direct effect on consumption expenditure in the absence of the e-commerce channel. To this end, we estimate a reduced-form regression of log MPCE on the external instruments using the HCES 2011-12 data. For ensuring the temporal consistency, we now construct cell tower density at the district level for 2010. The share of rural households with mobile phone ownership is drawn from Census 2011, which is the same variable used in our main specification. We include the full set of household and district-level controls, along with district-level nighttime light intensity measured in 2010, to absorb variation in local economic development. Table 4 presents the results. We find that both the coefficients of our instruments are statistically insignificant, which indicates that prior to the expansion of e-commerce platforms, digital infrastructure did not have any independent relationship with household consumption expenditure.

Table 4: Placebo test: Exclusion restriction

	Ln (MPCE)
Cell tower density	0.003
	(0.011)
Share HH with mobile ownership	0.129
	(0.084)
Observations	59,075

Notes: The table reports reduced-form OLS estimates using HCES 2011-12 data.
Standard errors are clustered at district level (in parentheses).
***, **, * denote significance at 1%, 5% and 10% level, respectively.

5.3.4 Alternative instrument variables

In another check, we use two alternate external instruments alongside internally generated instruments to validate the analysis. First, we instrument the variable of online purchases with the proportion of other households in the FSU that made online purchases. The proportion of households in the FSU making online purchases should not have a direct effect on the consumption expenditure of the household. Such an FSU-level variable that varies across the

households of an FSU has been used as a valid instrument in many contexts, especially in the context of adoption practices and sharing of information (Birthal et al., 2015; X. Li & Wang, 2025; Wang et al., 2025). The result in Column (1) of Table 5 show that online purchases are positively and significantly related to the MPCE of rural households, corroborating our initial findings.

Second, we construct a district-level digital readiness index along the lines of (Chen, 2026), who develops a multidimensional index to measure the district-level preparedness for digitalisation. The index comprises two broad dimensions: environment and readiness. The environment dimension captures the market and infrastructural conditions that support the penetration of ICTs at the district level, while the readiness dimension evaluates the extent of ICT use by households and businesses. The complete list of variables and data sources for each dimension is given in Appendix Table 7. We apply principal component analysis to aggregate the indicators within each dimension and obtain a normalised population-weighted digital readiness index. Column (2) of Table 4 reports the IV estimates, which confirm that the online purchases significantly enhance the consumption expenditure of rural households. Thus, the results are robust to both alternative instruments.

Table 5: Robustness analysis: Alternative IVs

	(1)	(2)
Online purchases	0.277***	0.166***
	(0.020)	(0.018)
Household characteristics	Yes	Yes
District characteristics	Yes	Yes
State fixed effects	Yes	Yes
Survey year fixed effects	Yes	Yes
Observations	306,804	306,506

Notes: The table reports the 2SLS estimates with both external and internally generated instruments. Columns (1) and (2) report the results with leave-one-out IV and the digital readiness index, respectively. The dependent variable is the log of MPCE. All specifications control for household characteristics, district characteristics, state fixed effects and survey year fixed effects. Standard errors are clustered at district level (in parentheses). ***, **, *denote the significance at the 1%, 5% and 10% level, respectively.

5.3.5 Propensity score matching (PSM)

As a final robustness check, we use propensity score matching (PSM) to provide an alternative estimate of the consumption effect of online purchases under the selection-on-observables assumption. PSM constructs a counterfactual group of households that are observationally similar to those making in online purchases. Accordingly, we first divide the sample into two groups, control (households that do not make online purchases) and treatment (household that make online purchases) and estimate propensity scores using a logit model based on household

characteristics. These scores are then used to match households using kernel matching and nearest neighbour matching algorithms. Based on the matched samples, we finally obtain the average treatment effect on the treated (ATT). The ATT represents the difference in MPCE between households engaging in online purchases and comparable households that do not.

Before discussing the results, we would like to highlight one caveat that the valid use of PSM requires to satisfy the balancing property. Figures 1 and 2 (Appendix) present the standardised mean differences and variance ratios across all covariates before and after matching for kernel and nearest neighbour matching, respectively. Prior to matching, several covariates show substantial differences between the treated and control groups. However, following matching, the standardised mean differences for all covariates converge to zero and the variance ratios approach unity. This indicates that the matched samples are comparable and that the balancing condition is satisfied.

Table 6 reports the ATT estimates. Column (1) presents the results based on kernel matching while Column (2) presents the results using nearest neighbour matching. The results from both matching algorithms are consistent and statistically significant at the 1% level. We find that households making online purchases have 15 percent higher MPCE compared to similar households that do not make online purchases. These findings are in line with the baseline estimates, reinforcing that online purchasing promotes household consumption expenditure.

Table 6: Robustness analysis: PSM

	(1)	(2)
Online purchases	0.152***	0.152***
	(0.004)	(0.004)
Household characteristics	Yes	Yes
District fixed effects	Yes	Yes
Survey year fixed effects	Yes	Yes
Observations	291,673	146,056

Notes: The table reports the average treatment effects on treated (ATT). Columns (1) and (2) report the results with ATT estimates from kernel and nearest neighborhood matching, respectively. The dependent variable is the log of MPCE. All specifications control for household characteristics, district and survey year fixed effects. Standard errors are clustered at district level (in parentheses). ***, **, *denote the significance at the 1%, 5% and 10% level, respectively.

6. Conclusion

This study quantifies the welfare gains from the expansion of e-commerce in the Indian economy, which now has third-largest base of online shoppers after China and the United States and huge potential to drive consumption growth through digital platforms. In recent years, the Government of India has also actively expanded digital infrastructure, enabling the delivery of goods and services across all postal codes. These developments are particularly important for rural areas, where households have historically faced constraints due to limited retail infrastructure and restricted market access. By reducing these geographic barriers, e-commerce has the potential to expand consumption opportunities, however, the extent to which these gains are realised remains an empirical question. In this context, we estimate the impact of online purchases on rural household consumption, measured in terms of MPCE and changes in the consumption basket. To best of our knowledge, this is one of few studies that has examined the effects of e-commerce on consumption for Indian economy. It contributes to the larger literature on the penetration of ICTs and its implications for household welfare.

Based on two cross-sectional rounds of HCES, we employ an instrumental variable approach for empirical analysis, wherein we combine the external instruments (district-level cell tower density and proportion of households with mobile ownership) with heteroscedasticity based instruments following the Lewbel (2012). This methodology provides more robust estimates when external instruments are weak. The findings reveal that online purchases significantly increase the MPCE among rural households. The category-specific effects show that online purchases raise the MPCE across all three categories including food, consumables and durables. However, the effect was more pronounced for durable goods. The evidence with regard to composition of consumption basket indicates that online purchasing led to reallocation of expenditure towards consumables and durable goods. These results suggest that e-commerce has created new consumption opportunities for products that were previously inaccessible to rural households. Finally, the mediation analysis using the CMS-T 2025 data demonstrate that households without ability to make online transactions are unable to avail the benefits of the digital economy.

These findings have important policy implications. First as we find that e-commerce promotes the consumption expenditure through the ability to make digital transactions, policies should focus on improving the digital literacy among households. The digital skill training programs can mitigate the perceived complexity of operating digital devices and help build trust in digital ecosystem. Second, based on our findings, we can say that digital infrastructure and digital literacy are complementary inputs. The expansion of connectivity in the absence of adequate digital literate

will yield limited returns. Thus, the policy efforts should jointly target access and capability formation. Lastly, to realise the full potential of e-commerce in rural areas, there is a need to prioritise the additional infrastructural improvements in terms of modernising logistics facilities, upgrading rural transportation systems and building smart warehousing hubs.

Like any empirical analysis, this study has certain limitations. First, the use of two rounds of cross-sectional survey data restricts the analysis to contemporaneous effects and does not allow us to examine the impact of transitioning to online purchasing. Panel data would enable a more precise identification of the causal effects of e-commerce expansion on consumption expenditure. Second, digital literacy is proxied by the ability to perform online transactions, which captures an important but limited dimension of digital capability. There are other dimensions such as information processing, platform navigation, and online trust, necessary to have the comprehensive measure for digital literacy but not observed in the survey data used. Third, although we address endogeneity concerns using an instrumental variables approach, the validity of the exclusion restriction cannot be directly tested and remains an identifying assumption.

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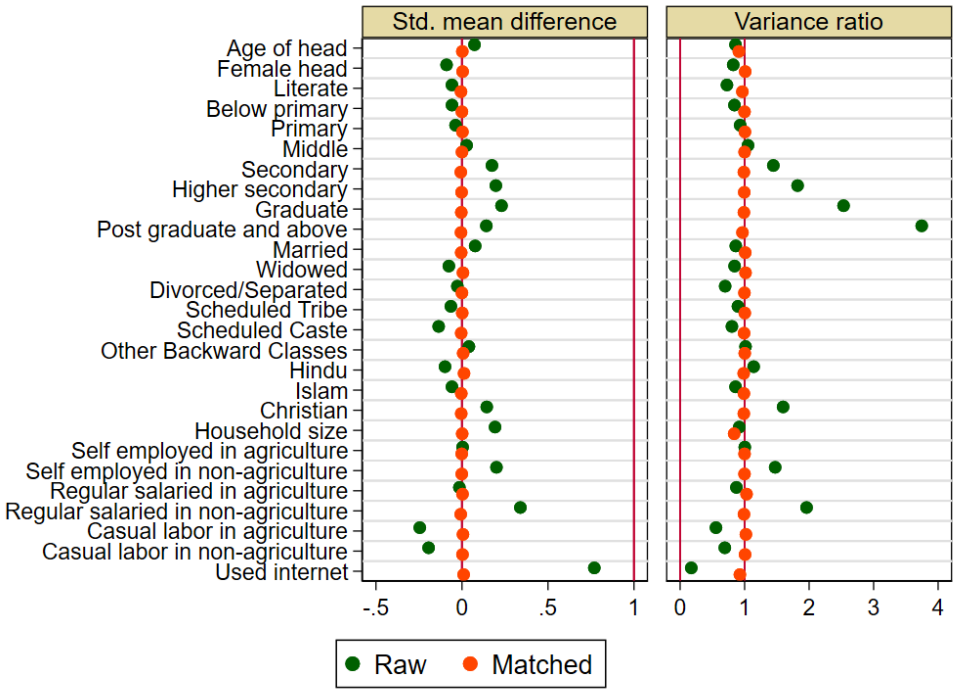
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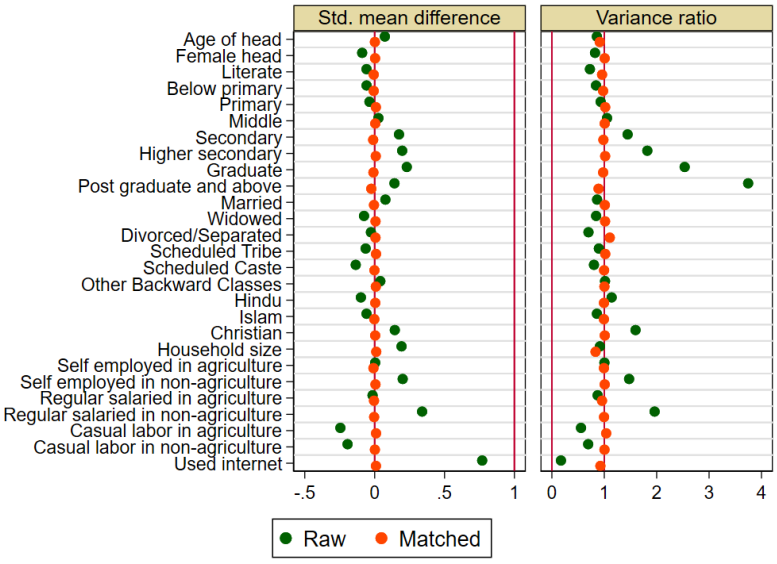
Appendix

Figure 1: Covariate Balance Before and After Matching (Kernel Matching)



Source: Author's calculation based on HCES 2022-23 and HCES 2023-24

Figure 2: Covariate Balance Before and After Matching (Nearest Neighbour Matching)



Source: Author's calculation based on HCES 2022-23 and HCES 2023-24

Tables

Table 1: Summary statistics

	Observations	Mean	Std Dev	Min	Max
	(1)	(2)	(3)	(4)	(5)
Dependent variables					
Log of MPCE	306818	8.282	0.476	5	12
Log of food MPCE	306743	7.531	0.453	1	12
Log of consumable MPCE	306805	7.301	0.609	2	12
Log of durables MPCE	306592	6.063	0.731	-0	11
Explanatory variable					
Online purchases	306818	0.309	0.462	0	1
Household characteristics					
Age of head	306818	48.979	13.873	4	120
Female head	306818	0.139	0.346	0	1
Literate	306818	0.033	0.178	0	1
Below primary	306818	0.089	0.285	0	1
Primary	306818	0.157	0.363	0	1
Middle	306818	0.153	0.360	0	1
Secondary	306818	0.128	0.334	0	1
Higher secondary	306818	0.076	0.265	0	1
Graduate	306818	0.049	0.215	0	1
Post graduate and above	306818	0.011	0.105	0	1
Married	306818	0.839	0.367	0	1
Widowed	306818	0.134	0.341	0	1
Divorced/Separated	306818	0.006	0.077	0	1
Scheduled Tribe	306818	0.182	0.386	0	1
Scheduled Caste	306818	0.197	0.398	0	1
Other Backward Classes	306818	0.411	0.492	0	1
Hindu	306818	0.784	0.411	0	1
Islam	306818	0.107	0.309	0	1
Christian	306818	0.069	0.254	0	1
Household size	306818	4.502	2.126	1	37
Self-employed in agriculture	306818	0.330	0.470	0	1
Self-employed in non-agriculture	306818	0.142	0.349	0	1
Regular salaried in agriculture	306818	0.012	0.110	0	1
Regular salaried in non-agriculture	306818	0.134	0.341	0	1
Casual labor in agriculture	306818	0.137	0.344	0	1
Casual labor in non-agriculture	306818	0.173	0.378	0	1

	Observations	Mean	Std Dev	Min	Max
	(1)	(2)	(3)	(4)	(5)
Used internet	306818	0.772	0.419	0	1
District characteristics					
Share of SC population	306818	316.344	173.036	0	1015
Share of ST population	306818	304.077	487.051	0	1994
Share of literate population	306818	1254.663	205.084	582	1795
Share of worker population	306818	825.666	132.935	522	1353
Instrumental variables					
Log of cell tower density	306818	5.696	1.565	0	11
Share of mobile ownership in rural areas	306818	0.476	0.146	0	1

Source: Author's calculation based on HCES 2022-23 and HCES 2023-24

Table 2: Robustness analysis by including district-level nighttime light intensity

	(1)	(2)	(3)	(4)
Online purchase	0.164***			
	(0.018)			
OP- food		0.184***		
		(0.022)		
OP- consumables			0.217***	
			(0.027)	
OP - durables				0.363***
				(0.027)
Household characteristics	Yes	Yes	Yes	Yes
District characteristics	Yes	Yes	Yes	Yes
FSU fixed effects	No	No	No	No
State fixed effects	Yes	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes
Observations	306,818	306,743	306,805	306,592
F-statistic	314.649	214.312	307.975	206.173
Kleibergen-Paap rk LM statistic	181.241	84.712	186.519	171.479
Kleibergen-Paap rk Wald F-statistic	27.529	19.617	34.181	36.926

Notes: OP stands for online purchases. Table present 2SLS estimates using external instruments (cell tower density and district-level share of mobile-only telephone ownership) and internally generated instruments following Lewbel (2012). The dependent variables are log monthly per capita expenditure on total, food, consumables, and durable goods, respectively. The explanatory variables are binary indicators equal to one if the household made any online purchase in the respective category. Standard errors are clustered at the district level in IV columns, reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table 3: First-Stage IV regression

	Online purchases
Cell tower density	0.028***
	(0.006)
Share of mobile ownership	0.165***
	(0.064)
Household characteristics	Yes
District characteristics	Yes
State fixed effects	Yes
Survey year fixed effects	Yes
Observations	306,818

Notes: The table reports the first stage results of IV estimation. 2SLS estimates with both external and internally generated instruments. The dependent variable is a binary indicator variable that takes value one if households make online purchases and zero otherwise. The specification control for household characteristics, district characteristics, state fixed and survey year fixed effects. Standard errors are clustered at district level (in parentheses). ***, **, *denote the significance at the 1%, 5% and 10% level, respectively.

Table 4: Effect of online purchases on household consumption expenditure

	OLS	IV
	(1)	(2)
Online purchases	0.126***	0.185***
	(0.002)	(0.021)
Household characteristics		
Age of head	0.002***	0.002***
	(0.000)	(0.000)
Female head	-0.015***	-0.037***
	(0.004)	(0.011)
Literate	0.024***	0.029***
	(0.004)	(0.009)
Below primary	0.020***	0.012**
	(0.003)	(0.006)
Primary	0.042***	0.040***
	(0.002)	(0.005)
Middle	0.065***	0.061***
	(0.002)	(0.006)
Secondary	0.096***	0.098***
	(0.002)	(0.007)
Higher secondary	0.131***	0.157***
	(0.003)	(0.012)
Graduate	0.196***	0.209***
	(0.004)	(0.012)

	OLS	IV
	(1)	(2)
Post graduate and above	0.256***	0.301***
	(0.008)	(0.020)
Married	-0.045***	-0.064
	(0.015)	(0.055)
Widowed	-0.036**	-0.045
	(0.015)	(0.052)
Divorced/Separated	-0.015	-0.010
	(0.018)	(0.054)
Scheduled Tribe	-0.124***	-0.163***
	(0.005)	(0.010)
Scheduled Caste	-0.105***	-0.099***
	(0.003)	(0.007)
Other Backward Classes	-0.049***	-0.052***
	(0.003)	(0.006)
Hindu	-0.037***	-0.038**
	(0.009)	(0.017)
Islam	-0.028***	-0.027
	(0.010)	(0.019)
Christian	-0.020*	-0.017
	(0.012)	(0.023)
Household size	-0.082***	-0.088***
	(0.001)	(0.001)
Self-employed in agriculture	0.054***	0.034*
	(0.005)	(0.018)
Self-employed in non-agriculture	0.049***	0.057***
	(0.005)	(0.020)
Regular salaried in agriculture	0.010	0.036
	(0.008)	(0.024)
Regular salaried in non-agriculture	0.072***	0.087***
	(0.006)	(0.022)
Casual labor in agriculture	-0.034***	-0.032*

	OLS	IV
	(1)	(2)
	(0.005)	(0.017)
Casual labor in non-agriculture	-0.020***	-0.018
	(0.006)	(0.019)
Used internet	0.088***	0.118***
	(0.002)	(0.006)
District Characteristics		
Share of SC population		-0.000**
		(0.000)
Share of ST population		-0.000***
		(0.000)
Share of Literate population		0.000
		(0.000)
Share of worker population		-0.000
		(0.000)
Constant	8.495***	
	(0.021)	
FSU fixed effects	Yes	No
State fixed effects	No	Yes
Survey year fixed effects	Yes	Yes
Observations	306,804	306,818
F-statistic	1616.422	329.888

Notes: Column (1) presents OLS estimates with FSU-year fixed effects. Column (2) presents 2SLS estimates using external instruments and internally generated instruments following Lewbel (2012). The dependent variable is log of MPCE. Standard errors are clustered at the FSU level in Column (1) and at the district level in Column (2), reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table 5: Category-specific effects of online purchases on consumption expenditure

	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
OP - food	0.098***	0.212***				
	(0.007)	(0.024)				
OP-consumable			0.174***	0.245***		
			(0.004)	(0.031)		
OP - durables					0.294***	0.368***
					(0.005)	(0.028)
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
District	No	Yes	No	Yes	No	Yes

characteristics						
FSU fixed effects	Yes	No	Yes	No	Yes	No
State fixed effects	No	Yes	No	Yes	No	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	306,729	306,743	306,791	306,805	306,577	306,592
F-statistic	935.635	204.688	1173.853	320.738	1056.750	202.482
Kleibergen-Paap rk LM statistic		85.451		186.125		171.980
Kleibergen-Paap rk Wald F-statistic		21.748		39.783		38.416

Notes: OP stands for online purchases. Columns (1), (3), and (5) present OLS estimates with FSU-year fixed effects and survey year fixed effects. Columns (2), (4), and (6) present 2SLS estimates using external instruments (cell tower density and district-level share of mobile-only telephone ownership) and internally generated instruments following Lewbel (2012). The dependent variables are log of monthly per capita expenditure on food, consumables, and durable goods, respectively. The explanatory variables are binary indicators equal to one if the household made any online purchase in the respective category. Standard errors are clustered at the FSU level in OLS columns and at the district level in IV columns, reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6: Effect of online purchases on composition of consumption expenditure

	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
OP- food	0.001	-0.008				
	(0.002)	(0.007)				
OP-consumables			0.020***	0.027***		
			(0.001)	(0.004)		
OP -durables					0.022***	0.021***
					(0.001)	(0.002)
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
District characteristics	No	Yes	No	Yes	No	Yes
FSU fixed effects	Yes	No	Yes	No	Yes	No
State fixed effects	No	Yes	No	Yes	No	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	306,804	306,818	306,804	306,818	306,804	306,818
F-statistic	277.244	94.092	187.872	88.529	227.357	45.083
Kleibergen-Paap rk LM statistic		85.461		186.140		172.038

	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Kleibergen-Paap rk Wald F-statistic		21.751		39.782		38.398

Notes: OP stands for online purchases. Columns (1), (3), and (5) present OLS estimates with FSU-year fixed effects and survey year fixed effects. Columns (2), (4), and (6) present 2SLS estimates using external instruments (cell tower density and district-level share of mobile-only telephone ownership) and internally generated instruments following Lewbel (2012). The dependent variables are share of total consumption expenditure on food, consumables, and durable goods, respectively. The explanatory variables are binary indicators equal to one if the household made any online purchase in the respective category. Standard errors are clustered at the FSU level in OLS columns and at the district level in IV columns, reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table 7: Variables used in PCA

Major category	Minor category	District-level variables	Data source
1. Environment	**Market Environment**	Share of establishments engaged in NIC=611 activity in rural areas	Sixth Economic Census (2013
		Share of establishments engaged in NIC=612 activity in rural areas	Sixth Economic Census (2013
		Share of establishments engaged in NIC=613 activity in rural areas	Sixth Economic Census (2013
	Infrastructure Environment	Share of rural households having telephones/cellphones/computers divided by share of urban households having telephones/cellphones/computer	Population Census (2011)
		Share of rural population having access to common service centers	Population Census (2011)
		Share of rural population having mobile phone coverage	Population Census (2011)
2. Readiness	**Individual Readiness**	Percentage of rural households with computers	Population Census (2011)
		Percentage of rural households having computers with internet connection	Population Census (2011)
		Percentage of rural households with telephone	Population Census (2011)
		Percentage of rural households with telephone	Population Census (2011)
	Business Readiness	ICT employees per 1,000 population in rural areas	Sixth Economic

			Census (2013)

Notes: NIC=611 is wired telecommunications activities; NIC=612 is wireless telecommunications activities; NIC=613 is satellite telecommunications activities. Common service centers are places where the government can deliver e-Service to people without access to computers or the Internet.