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Digital financial inclusion and transitory consumption: Household-level evidence from India

Abhishek Kumar [a,b], Sushanta Mallick [c,*], Apra Sinha [d]

[a] University of Southampton, Southampton, UK
[b] Centre for Social and Economic Progress, New Delhi, India
[c] Queen Mary University of London, London, UK
[d] University of Delhi, New Delhi, India

HIGHLIGHTS

- This study distinguishes between traditional and digital financial inclusion.
- Results show that digital inclusion is associated with higher transitory consumption, unlike traditional inclusion.
- The association between transitory consumption and digital inclusion is stronger at lower levels of wealth.
- Traditional inclusion is associated with a greater reduction in borrowing costs compared to digital inclusion.
- Oversensitivity of consumption from digital inclusion calls for digital literacy and curbs on predatory and unfair lending.

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ABSTRACT

Recent developments in FinTech have made financial inclusion a policy priority across the globe. Ex-ante, it is not clear whether the effect of digital financial inclusion on households would be similar to traditional inclusion. Using data from household surveys from India, we explore the relationship between financial inclusion and transitory consumption. Our results suggest that, unlike traditional inclusion, digital financial inclusion is associated with higher transitory consumption. However, when considering the distribution of wealth, we find that the association between transitory consumption and digital financial inclusion is stronger at lower levels of wealth. Finally, we explain this heterogeneous effect of digital and traditional financial inclusion by showing that households with traditional financial inclusion experience a greater reduction in borrowing costs compared to those with digital financial inclusion. The oversensitivity of consumption due to digital inclusion highlights the need for digital literacy and policies aimed at curbing predatory and unfair lending practices.

1. Introduction

Financial technology (Fintech) has advanced rapidly in recent years, expanding financial inclusion by lowering the costs and barriers to access, particularly for previously excluded households. As a result, digital financial inclusion has surged, operating increasingly on a different path from traditional financial inclusion channels such as bank branches and formal credit institutions. Despite this growth, there is a notable lack of empirical evidence on the relative roles of traditional versus digital financial inclusion in influencing household-level outcomes such as consumption. Understanding this distinction is critical, as the usefulness and effectiveness of these two measures of inclusion may differ substantially. Digital inclusion,[1] in particular, has been argued to promote compulsive, conspicuous, and impulsive buying behaviors through various digital platforms (Pellegrino et al., 2022).

It is important to distinguish between permanent consumption and observed consumption when evaluating the impact of financial inclusion on household consumption. Permanent consumption reflects a

* Corresponding author.
Email addresses: a.kumar@southampton.ac.uk; akumar@csep.org (A. Kumar), s.k.mallick@qmul.ac.uk (S. Mallick), aprasinha@south.du.ac.in (A. Sinha).

[1] Although this paper is about digital financial inclusion, it is expected that digital financial inclusion leads to other types of digital inclusion or vice-versa, such as social media and the internet, and hence also captures digitalization in general.

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household's consumption based on its permanent or expected long-term income (Friedman, 1957), whereas observed consumption combines permanent consumption with transitory shocks and short-term fluctuations. Theoretically, under conditions of market imperfections, financial inclusion could affect permanent consumption by altering long-term income or investment opportunities. However, empirical evidence supporting this channel is limited (Angelucci et al., 2015; Banerjee et al., 2015; Crepon et al., 2015; Jack & Suri, 2014). Instead, the primary empirical finding in the literature is that financial inclusion affects current consumption primarily by allowing households to smooth consumption in the face of shocks (Jack & Suri, 2014). Recent literature argues that mobile phone money transfer[2] allows users access to their wider risk-sharing networks and helps households smooth adverse shocks (Abiona & Koppensteiner, 2022; Batista et al., 2014; Blumenstock et al., 2016; Jack & Suri, 2014; Riley, 2018). In other words, financial inclusion mainly affects households by influencing transitory consumption. Therefore, we estimate the effect of traditional and digital financial inclusion on transitory consumption, helping to understand the role of these two measures of inclusion in the smoothing of consumption.

We use nationally representative household-level survey data from India that capture traditional and digital financial inclusion and make a clear distinction between these two measures of inclusion. This survey question related to the distinction is essential to compare the effect of traditional and digital financial inclusion on households, which is missing in the existing literature. Based on the evidence cited above, we assume that permanent consumption is not dependent on financial inclusion and estimate a measure of permanent consumption using detailed information about the households in the survey. We construct a consistent measure of household wealth from this and estimate the household-level permanent consumption using a model that includes a fourth-order polynomial in wealth and several household characteristics including age, education, religion, caste, geographical location, and occupation following the approach of Arrondel (2002); Guiso et al. (1992); Kazarosian (1997); King and Dicks-Mireaux (1982); Lusardi (1997); Xu and Yilmazer (2021) and relate it to the permanent income hypothesis of Friedman (1957). The underlying assumption is that transitory income shocks are random and not related to any of these household characteristics. We argue that these factors should be able to capture permanent consumption for a household and derive the transitory consumption—the difference between consumption and permanent consumption—based on Friedman (1957).[3] Using exogenous variation from the survey related to borrowing for medical emergencies and legal emergencies, we show that the estimated model gives us reliable transitory consumption and validates the empirical design. As expected, we find that the estimated transitory consumption is higher (more negative) for households that borrowed for medical emergencies in the survey year.

Thereafter, we estimate the effect of traditional and digital financial inclusion on the absolute value of transitory consumption. We use the absolute value because financial inclusion is expected to bring consumption closer to permanent consumption from both directions, and hence the absolute gap between consumption and permanent consumption should decline. An important assumption behind this regression is that transitory income shocks affecting households are not dependent on financial inclusion. In a cross-section, effectively this implies that financial inclusion is not a choice variable and is given. As argued above, financial inclusion should lower this absolute deviation and enable households to consume closer to their permanent consumption and reduce transitory consumption. We find that traditional financial inclusion is associated with lower transitory consumption, whereas digital financial inclusion is associated with higher transitory consumption. The effect of digital financial inclusion is similar to the findings of Agarwal et al. (2019) and Lai et al. (2020); Li et al. (2020). But inclusion alone is not sufficient for consumption smoothing. Due to imperfections in financial markets, households and firms face borrowing constraints and often collateral is required. Household wealth is an important source of collateral, and hence we estimate the state (wealth) dependent marginal effects of traditional and digital financial inclusion on consumption smoothing.

We estimate the marginal effects of traditional and digital financial inclusion on transitory consumption at different wealth quantiles. We find that digital financial inclusion leads to higher transitory consumption at low levels of wealth, and this suggests that the over-sensitivity of consumption to income, and overspending due to digital financial inclusion reported by Agarwal et al. (2019) and Lai et al. (2020) are prevalent at lower levels of wealth. Digital financial inclusion is effective in consumption smoothing at higher levels of wealth, as it lowers transitory consumption. Also, on average, traditional financial inclusion is associated with lower transitory consumption compared to digital financial inclusion.

For robustness, we estimate the counterfactual consumption (permanent consumption) for households with digital financial inclusion (treated) using propensity score matching. Specifically, we create a control group of households by applying propensity score and nearest-neighbor matching on all household characteristics mentioned above excluding digital financial inclusion. Intuitively, these households both treated and control are similar in all characteristics including traditional financial inclusion. This approach mitigates the omitted variable biases arising from regression based measure of permanent consumption used above. Under the assumption that digital financial inclusion does not affect permanent consumption and that transitory income shocks affecting households are independent of digital financial inclusion, the distribution of the consumption of the control group is counterfactual permanent consumption for households with digital financial inclusion. We argue that the difference between the observed consumption of households with digital financial inclusion and their counterfactual permanent consumption provides an alternative estimate of the transitory consumption attributable to digital financial inclusion. Notably this approach yields a similar effect for digital financial inclusion on transitory consumption. The matching only resolves concerns related to observables but concerns related to unobservables still remain. We use the proportion of households that use digital financial services (excluding the nodal household), as an instrumental variable for digital financial inclusion, Riley (2018) and Barry and Creti (2023). Digital inclusion of other households in a village captures the supply driven financial inclusion which should not be correlated with village level unobservables that affect both digital inclusion and consumption. These instrumental variables regression gives similar results and suggests that digital inclusion leads to higher transitory consumption.

We also estimate a model for the borrowing cost faced by households to explain state-dependent marginal effects of traditional and digital financial inclusion, and differences in the marginal effect of traditional and digital inclusion. Results suggest that traditional and digital financial inclusion reduce the borrowing cost, but the marginal effect of traditional financial inclusion on the borrowing cost is much higher compared to digital financial inclusion. This is consistent with the fact that on average traditional financial inclusion is associated with lower transitory consumption. These regression results also suggest that wealth is an important determinant of the borrowing cost conditional on traditional and digital financial inclusion. Hence, financial inclusion itself is not sufficient for fully utilizing the benefits of financial markets. At a higher level of wealth, the borrowing costs are lower enough for households to adjust consumption, and hence lower transitory consumption. These

[2] The digital inclusion measure used in this paper is the same as mobile money transfer technology being discussed in these papers.

[3] We treat this regression as predictive regression and do not attribute any causal meaning. This is also because even if financial inclusion does not affect permanent consumption, it affects consumption by design, and hence one can argue that the regression to estimate permanent consumption gives biased estimates if the inclusion is correlated with shocks affecting the households. We deal with this issue using a counterfactual estimator as explained later.

results together explain why the effectiveness of financial inclusion in lowering transitory consumption increases with wealth.

The plan of the paper is as follows. Section 2 provides a brief survey of related literature. Section 3 describes the survey data (77th round), which is based on nationally representative surveys undertaken by the National Sample Survey Office (NSSO) of the Government of India. Section 4 explains the theoretical rationale for the empirical exercises and presents the empirical framework. Section 5 presents the empirical results, followed by concluding remarks.

2. Literature review

This paper relates to four strands of literature. The first is evidence on the long-run effects of financial inclusion and financial development on aggregate outcomes, such as GDP growth, poverty, and consumption using aggregate and household-level data. Financial inclusion is important and it is widely believed that state-led financial inclusion tends to promote development and reduce poverty (Beck et al., 2007; Burgess & Pande, 2005). King and Levine (1993a) using a panel of countries argue that financial development predicts future growth. King and Levine (1993b) using a theoretical model show that financial development increases the probability of successful innovation, and hence accelerates the rate of economic growth. Rajan and Zingales (1998) argue that financial development can reduce the external finance premium for firms and induce growth. Levine (1997) present a systematic survey of the early literature on financial development and economic growth. Greater financial inclusion brings unbanked firms and consumers into the formal banking system, enabling financial institutions to diversify their depositor base and loan portfolio (Ahamed and Mallick, 2019).

The second strand of literature relates to the relationship between financial inclusion and permanent consumption at the household level. Macroeconomic models both Keynesian and New-Keynesian models, based on the permanent income hypothesis, imply no role for financial inclusion in influencing household consumption, albeit for different reasons. In traditional Keynesian models, consumption is dependent on income, and hence financial inclusion has no direct impact on consumption although it can affect consumption indirectly by influencing income. In traditional Keynesian models, households behave as hand-to-mouth or rule-of-thumb households and cannot do consumption smoothing. In the real business cycle and new Keynesian models, households can do consumption smoothing by buying and selling bonds, and the liability of one household is an asset for another household. This is also called perfect risk sharing. These models implicitly assume universal financial inclusion. A large recent literature suggests a limited role for financial inclusion in driving permanent consumption (Angelucci et al., 2015; Banerjee et al., 2015; Crepon et al., 2015; Jack & Suri, 2014). Some studies have also estimated the effect of financial inclusion on consumption (Agarwal et al., 2019; Lai et al., 2020). Biru et al. (2024) using a meta-regression, show that financial inclusion has a significant positive effect on household consumption.

The third strand of literature is on the role of financial inclusion in smoothing consumption. In other words, the effect of financial inclusion could depend on the nature of shocks, namely adverse and favorable, affecting households. Financial inclusion can affect the consumption of these two types of households differently. Households facing transitory adverse income shocks could have higher consumption due to financial inclusion compared to excluded households, and vice versa. Testing this requires exogenous variation in financial inclusion and identification of shocks affecting the household (Jack & Suri, 2014). The effect of traditional inclusion on consumption smoothing has also been explored extensively in the literature (Pomeranz & Kast, 2022; Somville & Vandewalle, 2023). Pomeranz and Kast (2022) and Somville and Vandewalle (2023) argue that traditional financial inclusion, i.e., access to banking, greatly improves consumption smoothing. Bhattacharya and Patnaik (2016) argue that financial inclusion can increase relative consumption volatility as households smooth the trend productivity shock; this leads to a larger change in current consumption, compared to an increase in current income. Compaore and Sawadogo (2025) using a sample of 28 countries identify three regimes based on the relationship between consumption volatility and financial inclusion and find that in the first regime, inclusion increases volatility, whereas in the second regime, inclusion reduces volatility with no effect in the third regime. A large literature suggests that households' ability to smooth adverse and favorable transitory shocks could be different (Bunn et al., 2018; Christelis et al., 2019; Deaton, 1992; Jappelli & Pistaferri, 2010).

Finally, this paper relates to a large emerging literature on digital financial inclusion and consumption smoothing (Abiona & Koppensteiner, 2022; Batista et al., 2014; Blumenstock et al., 2016; Jack & Suri, 2014; Riley, 2018). In recent times, there has been a surge in digital financial inclusion due to the development of Fintech which has led to higher growth in per capita GDP (Khera et al., 2022). Digital financial inclusion is expected to have fewer barriers in terms of wealth and income, and hence digital financial inclusion is likely to have significant micro and macro effects. Lai et al. (2020) argue that digital financial inclusion has diminished households' ability to insure against transitory income shocks. They suggest that it is driven by the over-sensitivity of consumption to income due to online purchases facilitated by digital financial inclusion. Agarwal et al. (2019) also argue that digital payments lead to overspending by households. Cavoli and Gopalan (2023) using aggregate data from 85 emerging and developing economies argue that financial inclusion does not lead to consumption smoothing. Contrary to these findings, Abiona and Koppensteiner (2022) argue that the adoption of mobile money leads to consumption-smoothing due to adverse shocks in Tanzania.

We compare the role of traditional and digital financial inclusion using nationally representative household survey data from India, which is largely missing in the literature. The survey clearly makes a distinction between traditional and digital inclusion, which is used in this paper to compare the role of these two types of inclusion that can influence transitory consumption. In the past decade, India has experienced a significant growth in both traditional and digital inclusion. The government of India ran a massive inclusion drive known as Jan Dhan Yojana in the second half of the 2010s. Under this Yojana, so far 579.1 million beneficiaries have been able to open bank accounts[4], and hence they are now traditionally included. Also, during this time, India has been leading the world in FinTech and has made digital inclusion very accessible for common people.

3. Data: India - Debt & Investment Survey, Jan–Dec 2019, NSS 77th round

We use data from two sources: the state-level data are obtained from the 'States of India database' from the Centre for Monitoring Indian Economy, which is also used to create state-level indices for aggregate analysis. The household-level data are obtained from a nationally representative 'All India Debt & Investment Survey' of 2019. This survey contains detailed information related to household characteristics.

The survey contains information about the financial inclusion of households that can help distinguish between traditional and digital financial inclusion. The traditional inclusion dummy takes the value 1 if the household (at least one member) has an account in a bank, post office, or non-banking financial company (NBFC) or holds a credit card. The digital inclusion dummy takes the value 1, if the household (at least one member) has an E-Wallet. It is important to clarify that a bank account is not required for E-Wallet. An e-wallet, in this survey, refers to an online service accessed through a cell phone that allows an individual to make electronic transactions via some "Mobile Application (mobile app)". Such transactions may include purchasing items on-line as well as transferring money to others. However, individual bank mobile apps (of PNB, SBI, ICICI, etc.) are not considered as e-wallet for this purpose,

[4] https://pmjdy.gov.in/.

Table 1
Individual level financial inclusion.

Digital Financial Inclusion	Traditional Financial Inclusion		Total
	No	Yes	
No	152,302	318,463	470,765
Yes	178	24,630	24,808
Total	152,480	343,093	495,573

Notes: Traditional inclusion is a dummy that takes the value 1 if the individual has an account in a bank, post office, non-banking financial company (NBFC) or holds a credit card. Digital inclusion is a dummy that takes the value 1 if the individual holds an E-Wallet.

but "Payments banks" like Fino Payments Bank Ltd, Airtel Payments Bank Ltd, India Post Payments Bank Ltd and Paytm Payments Bank Ltd, Aditya Birla Idea Payment Bank, Jio Payment Bank, etc. are included. Table 1 provides the distribution of these two inclusion measures for all households in the survey. As we can see, the prevalence of digital inclusion is less compared to traditional inclusion, and most of these digitally included individuals are traditionally included. Hence, to capture the effect of digital inclusion, we always include traditional inclusion. Also, all our regression estimates are at household level and a household has traditional (digital) financial inclusion if at least one member of the household has traditional (digital) financial inclusion.

Fig. 1 illustrates the distribution of household log consumption, segmented by traditional and digital inclusion, based on data from the household survey. The survey contains four questions related to consumption. 1. usual consumer expenditure in a month for household purposes out of purchase (A). 2. The imputed value of usual consumption in a month from home-grown stock (B). 3. The imputed value of usual consumption in a month from wages in kind, free collection, gifts, etc (C). and 4. expenditure on the purchase of household durables during the last 365 days (D). The usual monthly consumer expenditure is given by $[A+B+C+(D/12)]$, and we divide that by the size of the household, which is called household monthly consumption in this paper. The distribution reveals a clear pattern: households with any form of inclusion, whether traditional or digital, exhibit higher consumption levels than those without inclusion.[5] This is evident as the consumption distribution of included households shifts to the right compared to excluded ones, reflecting greater purchasing power or access to resources. However, the distinction between traditional and digital inclusion is even more pronounced. The consumption gap between households with digital access and those without is substantially wider than the gap between traditionally included and excluded households.

We have information related to the value of land and buildings, livestock, transport equipment, and farm and non-farm equipment. We also have information related to financial assets such as deposits and financial liabilities (loans) of households. Using this detailed information, we construct a consistent measure of household wealth. Interestingly, when we turn to wealth differences, as shown in Fig. 2, the pattern gets reversed. The average wealth gap between households with digital access and those without is substantially lower than the gap between traditionally included and excluded households. In other words, the consumption difference driven by digital inclusion is associated with a very low wealth differential compared to the consumption difference driven by traditional inclusion. Fig. 3 sheds further light on the driving forces behind these trends in digital inclusion. It reveals that much of the consumption gains linked to digital inclusion are not just due to having digital access, but to actively using it. This suggests that the economic advantages of digital inclusion are primarily realized by households that engage with digital platforms, services, and tools, rather than simply being part of the digital network.

Although inclusion is leading to higher consumption, it is not clear whether higher consumption due to inclusion is arising from smoothing adverse shocks or overconsumption due to inclusion as argued by Lai et al. (2020) and Agarwal et al. (2019). Therefore, in this paper, we estimate the effect of financial inclusion on transitory consumption or consumption smoothing. This requires knowledge of a measure of permanent and actual household consumption. Actual consumption is provided in the survey, and we obtain a measure of permanent consumption as described in the next section.

The survey contains the caste and religion of these households, and this is useful to capture the heterogeneity in household consumption. Munshi (2019) argues that caste plays an important role in all aspects of human lives in India. This is used to create indicator variables for caste and religion to capture heterogeneity in consumption across caste and religion. We have the ages of all the members of the household. We include six variables based on age and education to capture the age-earning/consumption profile of the household, while estimating permanent consumption. We use the highest age in the household, the sum of the ages of all household members, the highest level of education, the age of the person having the highest level of education, the sum of years of education of household members, and the number of household members. For these six variables we only consider household members older than 14 years as we want to capture age based earning and consumption profile.

The information related to education level given in Table 2 is used to create indicator variables for education and years of education. The survey only provides the education category and we create education years based on this as given in Table 2. We do this because we use two variables related to education. First is the highest category of education of the household member in the age group greater than 14. This is because in many households the maximum years of education belong to members having age less than 14. But this does not represent the earning potential of the household.[6] This is because people of age less than 14 are not legally allowed to work. Second is the sum of education years for all members of the household.

The survey also provides the job type of the household in rural and urban areas as given in Table 3 and this is used to create a consistent measure of household occupation across rural and urban areas. The job-type of the household is important in capturing the variation in permanent income across households.

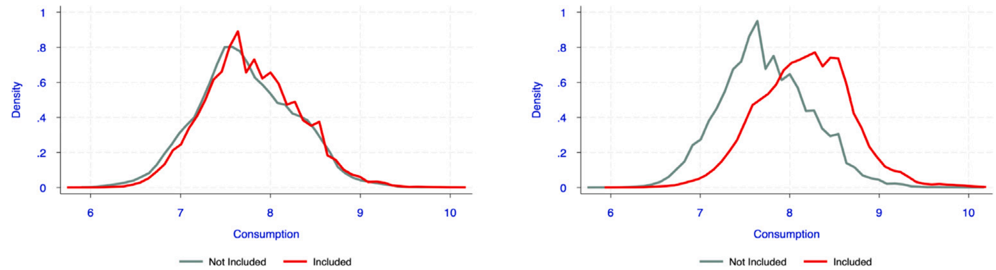
The survey also contains the information related to borrowings (amount) by the household, the corresponding agency/institution, the rate of interest paid by the household, the year and the purpose of these borrowings. The households may have multiple borrowings. We use the borrowings for medical emergencies in the survey year as an exogenous variation that will affect transitory consumption to show the validity of the empirical strategy. We have 106,032 observations on borrowings for the households and the % observations of borrowings from different agencies are given in Fig. B.1 in the appendix. 29.6% of the borrowings are from the scheduled commercial banks followed by 17.5% from relatives and 14.7% from professional money-lenders. We classify the borrowings from scheduled commercial banks, regional rural banks and co-operative banks as borrowings from banks.

All other remaining categories except borrowing from input suppliers and family & friends are considered as non-bank.[7] We winsorize the

[5] A similar positive relationship is obtained between state-level variables as well and has been reported in the online Appendix A.

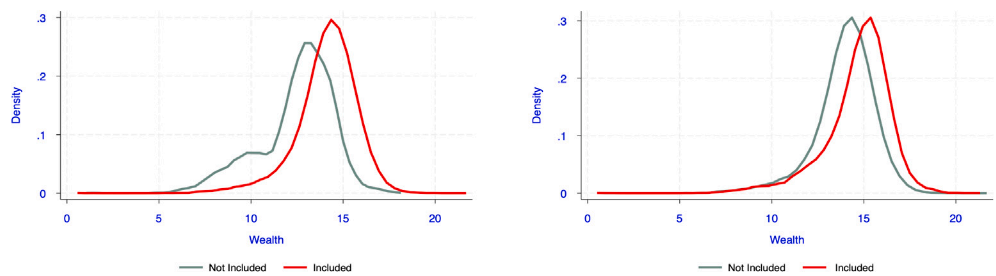
[6] There are many households in India in which we have a first-generation kid going to school, and in these households the highest level of education belongs to kids less than 14 years of age. In these households, the level of education of the child is not likely to be reflective of their earning capacity, and hence, we apply this cut-off to find the highest level of education.

[7] Based on the definition of formal financial inclusion used in this paper, these are also borrowings by financially included households. Other sources of borrowings such as from insurance companies and financial institution do not represent the borrowings by the financially included households. As a robustness, we include insurance companies, financial corporations/institutions and



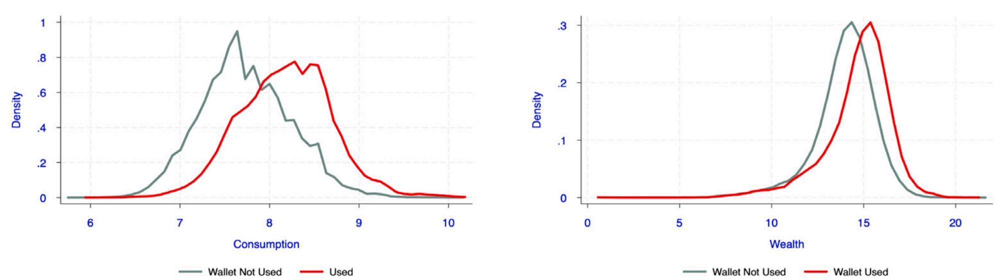
(a) Traditional Inclusion (b) Digital Inclusion

Fig. 1. Financial inclusion and log monthly consumption.



(a) Traditional Inclusion (b) Digital Inclusion

Fig. 2. Financial inclusion and log wealth.



(a) Consumption (b) Wealth

Fig. 3. E-Wallet Use, consumption and wealth.

Table 2
Education.

Education Category	Education Year
Not literate	0
Below primary	2.5
Primary	5
Upper primary/middle	8
Secondary	10
Higher secondary	12
Diploma/certificate course (up to secondary)	11
Diploma/certificate course (higher secondary)	13
Diploma/certificate course (graduation & above)	15
Graduate	15
Postgraduate and above	17

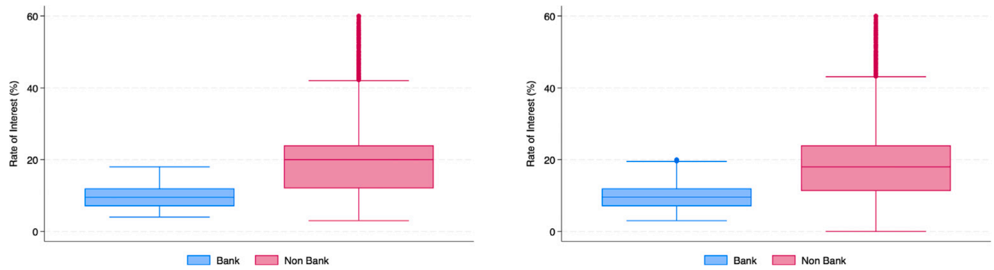
Table 3
Job type/household occupation.

Rural	Urban
Self-employed in agriculture	Self-employed
Self-employed in non-agriculture	Regular wage/salary earning
Regular wage/salary earning	Casual labour
Casual labour in agriculture	Other
Casual labour in non-agriculture	
Other	

interest rate in the respective category at 10% and 5%. Since households may have more than one borrowing, we use the individual interest payments and borrowings for these households to calculate the effective borrowing rate. Fig. 4 gives the distribution of the borrowing cost from bank and non-bank sources. As we can see, the median borrowing rate from banking sources is almost half of the median borrowing rate from non-banking sources. We also estimate a regression model to determine the marginal effect of inclusion on the cost of borrowing where we focus on digital financial inclusion.

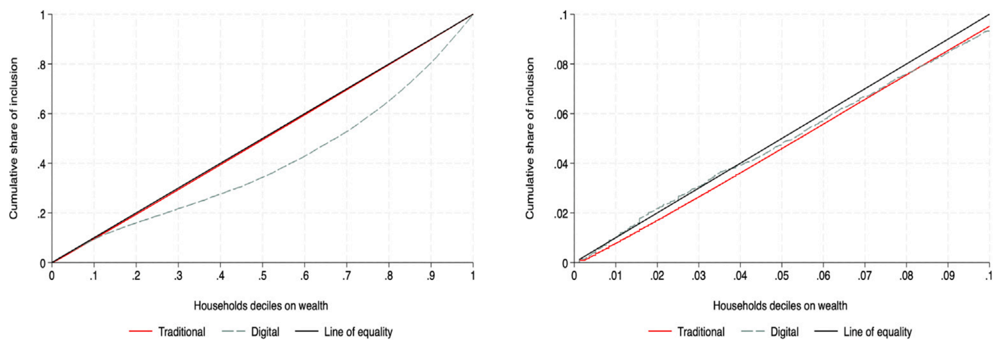
We find significant differences in the distribution of digital and traditional financial inclusion across wealth levels. We rank households according to their wealth and create deciles, and for each wealth decile,

NBFC's including micro-financing institutions (MFIs) into the category of banks and create formal and informal costs of borrowings. This also represents a similar distribution of the cost of borrowing from formal and informal sources.



(a) Borrowing Cost I (b) Borrowing Cost II

Fig. 4. Cost of Borrowing: We classify the borrowings from scheduled commercial banks, regional rural banks and co-operative banks as borrowings from banks. All other categories except borrowing from input suppliers and family & friends are considered as non-bank borrowings. The left panel shows the cost of borrowing winsorized at 10% in both tails and the right panel shows the cost of borrowing winsorized at 5% in both tails.



(a) Wealth Inequality in Inclusion (b) Wealth Inequality in Inclusion

Fig. 5. Wealth inequality in inclusion: We rank households according to their wealth and create deciles, and for each wealth decile we calculate the proportions of households that are financially included. The traditional inclusion dummy takes the value 1 if the household (at least one member) has an account in a bank, post office or non-banking financial company (NBFC) or holds a credit card. The digital inclusion dummy takes the value 1 if the household (at least one member) holds an E-Wallet. Wealth is the sum of the values of land and buildings, livestock, transport equipment, farm and non-farm equipment and deposits minus loans of the household.

we calculate the proportions of households that are financially included. This implies that if each wealth decile contains 10% of the inclusion then the wealth inequality in inclusion would be absent. This does not mean that everyone is included; it only implies that the inequality is evenly distributed across wealth deciles. The red line in Fig. 5(a) suggests that in the bottom wealth deciles, the proportion of traditional inclusion is lower than the corresponding proportion that would imply the absence of wealth inequality in inclusion; this is more evident in a microscopic view of the first decile given in Fig. 5(b). But unlike traditional inclusion, we find that lower deciles have a higher proportion of digital inclusion. But in the middle wealth deciles, this decreases. These two figures suggest that at the bottom decile of wealth, digital inclusion is more prevalent compared to the other deciles. This does not necessarily mean that these households are not traditionally included. But this highlights important heterogeneity among households due to wealth, as digital inclusion is significantly less evenly distributed across wealth deciles unlike traditional inclusion. We show in this paper that this has significant implications for transitory consumption. Appendix B at the end provides more information related to the relationship between consumption, financial inclusion, and household characteristics.

4. Empirical framework

We aim to estimate the difference between actual and permanent consumption and the role of financial inclusion in influencing the magnitude of this deviation, which is transitory consumption. One would expect that financial inclusion could lower the gap between actual and permanent consumption and thereby help smooth consumption. Including financial inclusion in the consumption regression is problematic due to two reasons. First, imagine that households are facing favorable shocks, then the excluded households will have higher consumption than the included ones, and the coefficient of inclusion is negative. On the other hand, if households face adverse transitory shocks, then the consumption of included households would be higher than excluded households and the inclusion coefficient would be positive. Hence, the coefficient of financial inclusion in a regression is dependent on the transitory shocks affecting the households. Despite the opposite effect of inclusion on consumption depending on shocks, financial inclusion will always bring the actual consumption closer to the permanent consumption independent of shocks, Fig. 6. It is important that we do not ex-ante know the shocks affecting households. Hence if we know the permanent consumption, then we can find the deviation of consumption from permanent consumption and test whether inclusion leads to lower transitory consumption.

Second, we expect that the effect of financial inclusion on transitory consumption is asymmetric. A large body of literature argues that households are better able to smooth positive shocks than negative shocks (Bunn et al., 2018; Christelis et al., 2019; Deaton, 1992; Jappelli & Pistaferri, 2010). In the model with liquidity constraints, consumption responds asymmetrically to transitory shocks because the ability to smooth unexpected and transitory income declines through borrowing can be seriously affected. Hence, including financial inclusion in the regression is not appropriate to capture the asymmetric effect. On the other hand, if the main constraint is participation in the financial markets, then the included households would be better able to manage negative shocks than excluded households. Hence, we calculate transitory

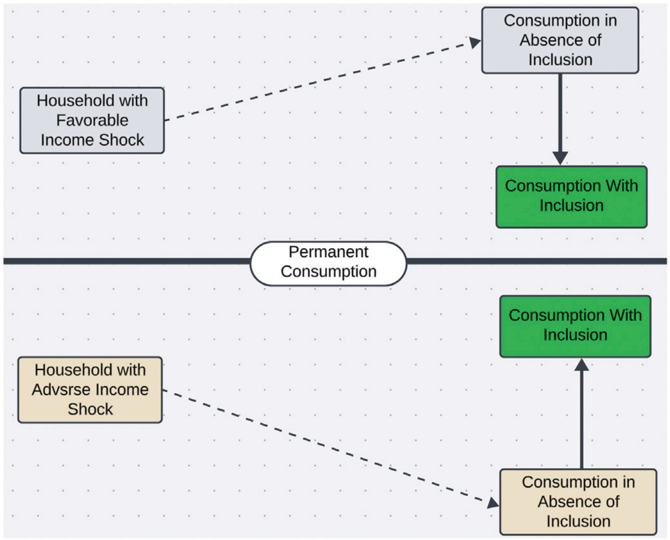


Fig. 6. Financial Inclusion, actual consumption and permanent consumption.

consumption at the household level and estimate the effects of financial inclusion. We adopt a two stage regression which is very popular, Chen et al. (2018). In the first stage, we estimate the permanent consumption and use that to obtain transitory consumption (absolute difference between consumption and permanent consumption).

Following Arrondel (2002); Beck et al. (2007); Guiso et al. (1992); King and Dicks-Mireaux (1982); Lusardi (1997), and Xu and Yilmazer (2021), the permanent income for the household is given by Eq. (1):

$$ln\left(Y_i^P\right) = Z_i\gamma + \theta_i + c(A_i) \tag{1}$$

where Z_i is a vector of observables such as education and occupation, θ_i is the variable measuring unobservable characteristics such as skill, and has variance σ_θ^2 and mean 0. θ_i is a household fixed effect and assuming zero mean for fixed effects is innocuous as this is implicit in the statistical models with fixed effects. $c(A)$ is a cohort effect which reflects the fact that for a given Z, younger generations are better off than their elders because of technical progress and capital accumulation. We capture $c(A)$ using the age of the members of the household with the highest education, the highest age in the household and the sum of the ages of all the members of the household, which also allows us to capture age earning profile over the life cycle. The most general version of the permanent income hypothesis linking permanent consumption and income according to Friedman (1957) can be written as Eq. (2):

$$c_i^P = \alpha_i Y_i^P \tag{2}$$

where c_i^P is permanent consumption and Y_i^P is permanent income. Each household has a different ratio of permanent consumption to income (α_i) which depends upon household characteristics such as the rate of borrowing and lending and preferences for consumption versus additions to wealth, Friedman (1957). Taking the log of the above and using $ln(\alpha_i) = s_i$, we can write the log of permanent consumption as given by Eq. (3).

$$ln\left(c_i^P\right) = s_i + ln\left(Y_i^P\right) \tag{3}$$

where we assume s_i has zero mean and variance σ_s^2. Also we assume that s_i is uncorrelated with θ_i. This implies that factors driving differences in permanent income across households could be different from factors driving the gap between permanent consumption and income across households. This assumption is justified because these two could be driven by different characteristics of the household as argued above.

The actual consumption (c_i) can be different from permanent consumption (c_i^P) due to transitory consumption (u_{it}) as given by Eq. (4).

$$ln\left(c_{it}\right) = s_i + ln\left(Y_i^P\right) + u_{it} \tag{4}$$

where we have $E(u_{it}) = 0$; $E(u_{it})^2 = \sigma_u^2$. We assume that s_i i.e., the log difference between permanent consumption and income is not correlated with deviation of actual consumption from permanent consumption, i.e., u_{it}. This is a reasonable assumption given the differences in sources of these two; s_i is a time invariant characteristic of the household, whereas u_{it} is a transitory shock affecting the household. u_{it} is 0 for households having consumption same as permanent consumption, $u_{it} > 0$ for households having consumption more than permanent consumption and $u_{it} < 0$ households having consumption less than permanent consumption. We test whether financial inclusion helps in keeping consumption close to permanent consumption, and hence reduces $|u_{it}|$. Using the above, we can write the main estimating equation given by

$$ln\left(c_{it}\right) = Z_i\gamma + c(A_i) + \theta_i + s_i + u_{it} \tag{5}$$

As we can see from the above equation, there are two types of household fixed effects influencing the consumption apart from the transitory consumption u_{it}. The first one is θ_i which causes variation in household permanent income and the second one is s_i which causes variation in permanent consumption to income ratio across households. These two fixed effects may not necessarily be the same and require panel data on income and consumption for estimation. Given the independence and zero mean assumption, these two fixed effects can be combined into one fixed effect $\phi_i = \theta_i + s_i$ where $E\left(\phi_i\right) = 0$ and $E\left(\phi_1^2\right) = \sigma_\phi^2$. In other words, since these two fixed effects are independent, they are observationally equivalent to a single fixed effect ϕ_i.[8] Since we have cross-section data, we cannot estimate the model with fixed effects. We estimate Eq. (6) as follows:

$$ln\left(c_i\right) = Z_i\gamma + c(A_i) + v_i \tag{6}$$

where $v_i = \phi_i + u_i$. Estimating Eq. (6) gives us the transitory component of consumption v_i.[9] Z includes the social group, religion, and education category of the household member aged 14 years or older with the highest level of education. It further includes the total years of education of all household members aged 14 years or older; the age of the oldest household member aged 14 years or older; the age of the household member aged 14 years or older with the highest level of education; the sum of ages of all household members aged 14 years or older; geographical location of the household (village/ward); a fourth-order polynomial in household wealth; and household occupation. We assume

[8] As argued above, these two fixed effects capture different household characteristics and should not be related. But this is not crucial for identification. The crucial assumption is $E\left(\phi_i, u_{it}\right) = E\left(\theta_i, u_{it}\right) = E\left(s_i, u_{it}\right) = 0$.

[9] Given the assumption that ϕ_i and u_i are not correlated, we can obtain the minimum variance estimator for ϕ_i given v_i. This is the approach in King and Dicks-Mireaux (1982). The minimum variance estimator is given by $\phi_i = \alpha \times v_i$ where $\alpha = \frac{\sigma_\phi^2}{\sigma_\phi^2+\sigma_u^2}$. We observe v_i from Eq. (6), but α is not known. King and Dicks-Mireaux (1982) use $\alpha = 0.5$. In the absence of a precise value of α from India, we use a range of $\alpha \in (0, 1)$ to capture all potential values of α. Hence we estimate Eq. (6) and obtain estimators for γ and $c(A_i)$. Using these estimates and v_i, we first estimate $\theta_i + s_i$ and then we obtain $u_i = v_i - \left(\theta_i + s_i\right)$ which is the deviation of consumption from permanent consumption. This serves as a good sensitivity analysis and shows the robustness of our results in the absence of panel data. It is important to mention that different values of α i.e., different assumptions about household fixed effects, imply a linear transformation of the transitory component and hence the directional effect of the variables in the second stage using v_i as dependent variables is not affected by the choice of α but the magnitude of these effects depends on α. Therefore we do not report these additional results in the paper as we are examining the differences in directional effects.

that permanent consumption does not depend upon financial inclusion. We use per-capita consumption and also multiply log consumption by 100 while estimating the models.

We assume that permanent consumption is dependent on wealth, and historical factors such as caste and religion, see Gupta et al. (2018). Charles et al. (2009); Khamis et al. (2012) and Kaus (2013). In a cross section of households facing both adverse and favorable shocks, the error term from the above regression should provide a measure of the transitory consumption for the household. The predicted consumption is equivalent to the permanent consumption. The actual consumption could differ from this, and there is a deviation of actual consumption from predicted permanent consumption. We estimate the effect of financial inclusion on transitory consumption or consumption smoothing. The intuition is that financial inclusion will enable households to consume close to their permanent consumption and will lower the deviation. Hence we take the absolute value of the deviation and regress it on inclusion variables as given by Eq. (7):

$$abs|v_i| = \theta_1 \text{ Digital Financial Inclusion}_i + \theta_2 \text{ Traditional Financial Inclusion}_i + \xi_i \tag{7}$$

Usually, consumption smoothing is used to describe the smoothing of consumption by households overtime, and since we use a cross sectional dataset, it is important to clarify this. We argue that some households are able to consume close to their permanent consumption predicted by the factors mentioned above, and these households are able to smooth consumption or have lower transitory consumption, whereas other households have actual consumption with a large deviation from permanent consumption and these households are not able to smooth consumption as much as the previous households and have higher transitory consumption. We aim to estimate the role of financial inclusion in driving this deviation. The identification relies on the fact that in a large cross section such as the one used in this dataset, households will face both adverse and favorable shocks at any level of wealth, occupation, social status and religion, and hence the regression will produce a measure of permanent consumption.

Since we estimate the model for households having positive wealth only, there is a non-random sample selection. The selection process could be correlated with consumption, and hence leading to biased and inconsistent estimates. We estimate a selection equation (probit model) that predicts the likelihood of a household being included in the sample, and incorporate a correction term (the inverse Mills ratio (IMR)) into the main outcome Eq. (6) to adjust for the non-random sample selection and estimate Eq. (8) and again estimate Eq. (7) using the absolute value of residuals from Eq. (8):

$$ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i \tag{8}$$

Above estimates have been obtained assuming that permanent consumption does not depend on financial inclusion, the financial inclusion is likely to influence consumption, as it helps in consumption smoothing, and hence in the absence of financial inclusion, the estimated γ and $c(A_i)$ from 6 and 8 could be biased. Therefore, we estimate another model given by Eq. (9) in which we also include the traditional financial inclusion. We believe that this regression has weaker assumption, as it assumes that permanent consumption does not depend upon digital financial inclusion alone.

$$ln\left(c_i\right) = Z_i\gamma + c(A_i) + \text{Traditional Financial Inclusion}_i\omega + v_i \tag{9}$$

We are agnostic about the sign of ω. ω captures the difference in consumption between two households included and not included conditional on permanent consumption. If these households are facing negative shocks, then the included household will have ω positive, and the transitory component less negative. On the other hand, if these households are facing positive shocks, then the included household will have ω negative, and the transitory component less positive. On the other hand, if conditional on Z, households are facing both the shocks as argued before, then the sign of the coefficient depends upon the distribution of inclusion across these two groups of households. Again we estimate γ and $c(A_i)$. Using these estimates, we obtain v_i and estimate the model given by Eq. (10).

$$abs|v_i| = \theta_1 \text{Digital Financial Inclusion}_i + \xi_i \tag{10}$$

In this regression, we only estimate the effect of digital inclusion on transitory consumption. All the above estimates are based on regressions where financial inclusion both traditional and digital or digital financial inclusion can be argued as an omitted variable. This is because even if we assume that financial inclusion does not affect permanent consumption, by design it affects consumption and hence the above estimates could be biased. To mitigate concerns related to omitted variable bias, we implement a counterfactual estimator. Specifically, we construct a control group using propensity score and nearest-neighbor matching on all household characteristics except digital financial inclusion, ensuring that treated and control households are similar on all other dimensions including traditional inclusion. Assuming that digital financial inclusion does not affect permanent consumption and that transitory income shocks are independent of digital financial inclusion, the control group's consumption distribution serves as the counterfactual permanent consumption for digitally included households. Importantly, this matching approach avoids the potential biases of the regression-based estimates of permanent consumption used earlier to some extent. We interpret the absolute gap between the actual consumption of digitally included households and their counterfactual permanent consumption as an alternative estimate of the transitory consumption caused by digital financial inclusion. We do not implement this method for traditional inclusion due to sample issues. We have very few less than 2% households without traditional inclusion and hence it is difficult to match 98% of households having traditional inclusion to appropriate control households without traditional inclusion.

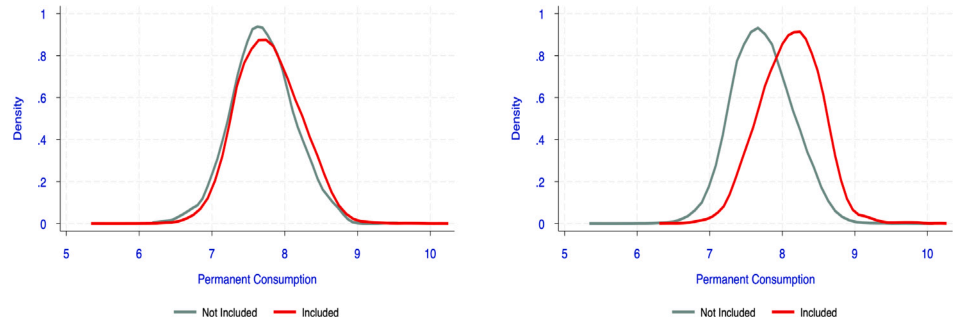
5. Results and analysis

5.1. Permanent consumption

As mentioned in the previous section, we first estimate permanent consumption of the household, given their characteristics, which is used to obtain an estimate of transitory consumption. Fig. 7(a) and (b) show the distribution of permanent consumption across different types of inclusion. It is important to mention that we did not include inclusion in estimating permanent consumption, yet we find that the distribution of permanent consumption differs across households based on inclusion. In other words, the households with inclusion have higher permanent consumption than excluded households and this is more evident in the case of digital inclusion. The main point is that this is a reasonable counterfactual for household permanent consumption and the deviation from this can be considered as transitory consumption which we show in the next section.

5.2. Threat to Identification: is transitory consumption reliable?

In the previous section, we argued that deviation of consumption from permanent consumption conditional on social status, religion, education category, sum of years of education of all the members of the household, age of the oldest person in the household, age of the person having the highest level of education, sum of ages of all the household members, geographical location of the household (village/ward), fourth order polynomial in wealth and job type of the household gives the transitory consumption. We show that it is indeed the case. We use a survey question that asks the household whether they borrowed for a medical emergency in the survey year. Consumption is available for the same year.



(a) Traditional Inclusion and Log Permanent Consumption (b) Digital Inclusion and Log Permanent Consumption

Fig. 7. Inclusion and Permanent Consumption: Permanent consumption is expected consumption obtained from $ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i$. We include a fourth-order polynomial in household wealth, social status, religion, the household's job type, and geographical location (village/ward). Additional controls include the number of household members aged 14 years or older; the highest education category among them; the age of the household member with the highest education category; the maximum age; the sum of ages; and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, job type of the household, and geographic location of the household.

Table 4
Borrowing for medical emergency and transitory component.

	(1) Absolute Transitory Component	(2) Absolute Transitory Component
Constrained Households	1.161*	1.139*
	(2.07)	(2.03)
Observations	100,663	100,663

Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance level respectively. Constrained households (an indicator variable which is 1 for households that borrowed for medical emergency) is the coefficient of constrained households from $\text{abs}v_i = \beta_0 + \beta_1\text{Constrained}_i + \xi_i$. v_i for the first column is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + v_i$ and for the second column is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i$. We include fourth order polynomial in wealth, social status, religion, the household's job type, and geographical location (village/ward). Additional controls include the number of household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category, the maximum age, the sum of ages, and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, job type of the household, and geographic location of the household.

Table 4 gives the results from a regression model in which we regress the absolute transitory component on an indicator variable which is 1 for households that borrowed for a medical emergency. This is available in the survey as the survey includes all the borrowings, their purpose and the year of borrowing. We only consider borrowing for medical purposes in the year 2019 which is the survey year. As expected, we find that the absolute transitory component is larger for these households.[10] It is important to mention that we did not include the borrowing characteristics in the regression model because there are many other reasons that could lead to transitory consumption which we do not observe. Since borrowing for a medical emergency is almost exogenous and the transitory consumption is larger for these households compared to all other households conditional on Z, we argue that Eq. (6) is able to identify the transitory component.[11]

5.3. Financial inclusion and transitory consumption

Table 5 gives the baseline results for consumption smoothing for total consumption. As we can see, the coefficient of traditional inclusion is negative and significant for total consumption. This suggests that traditional inclusion helps only in smoothing consumption, or traditional inclusion is associated with lower transitory consumption. Contrary to traditional inclusion, the coefficient for digital inclusion is positive and significant and this implies that digital inclusion adversely affects consumption smoothing or is associated with a higher transitory component. This is similar to the findings in Lai et al. (2020) and Agarwal et al. (2019).

Lai et al. (2020) argue that digital financial inclusion leads to oversensitivity of consumption to income due to online purchases facilitated by digital financial inclusion. Agarwal et al. (2019) also argue that digital payments lead to overspending by households. The difference between the coefficients of digital and traditional inclusion suggests a difference in the sensitivity of consumption due to digital and traditional inclusion, as they should not have differential sensitivity to permanent consumption. This heterogeneity in transitory consumption due to traditional and digital inclusion is unlikely to be driven by unobserved factors. This is because other unobserved factors which may affect permanent consumption are not expected to have a different relationship with these two measures of financial inclusion. Since we use the generated regressor, the traditional standard errors could be problematic and hence we use the bootstrap method and obtain the coefficients of inclusion measures and corresponding standard errors. These are given in Fig. 8 and we present similar results as given in Table 5. Since the results are the same, we report the remaining results in this paper using traditional standard errors only.

Next, we analyse the marginal effect of traditional and digital inclusion on transitory consumption across wealth quartiles. This is important because mere inclusion will not allow households to borrow and smooth consumption. Most of the time borrowings are subject to collateral constraints, and wealth is an important collateral. Table 6 gives the marginal effect of digital and traditional inclusion on total consumption across

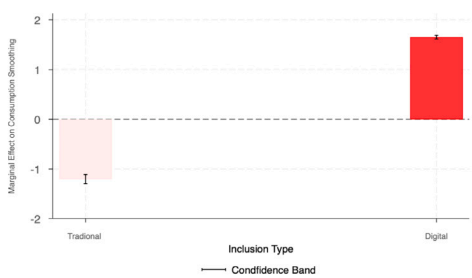
[10] Also the transitory component is more negative for these households. A simple regression where we include the indicator variable in model 6 gives a negative and significant coefficient for this indicator variable suggesting that these households indeed have lower consumption.

[11] We find similar results if we use another survey question related to borrowing for a legal emergency which is given in Table C.1 in the appendix.

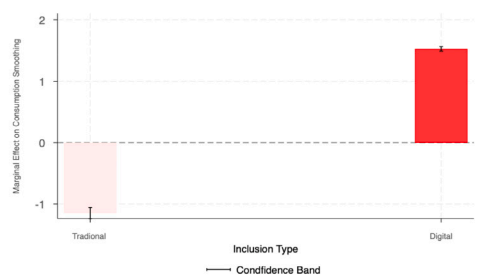
Table 5
Inclusion and absolute transitory consumption.

	(1) Transitory Consumption	(2) Transitory Consumption	(3) Transitory Consumption	(4) Transitory Consumption
Digital Inclusion	1.632***	1.506***	1.708***	1.551***
	(9.18)	(8.54)	(9.59)	(8.80)
Traditional Inclusion	−1.227*	−1.170*	−1.189*	−1.117*
	(−2.52)	(−2.41)	(−2.45)	(−2.32)
Observations	100,663	100,663	100,663	100,663

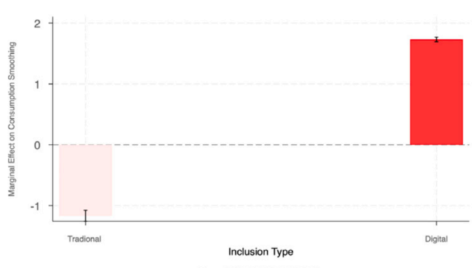
Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance level respectively. The reported coefficients are from $\text{abs}v_i = \beta_0 + \beta_1 \text{Traditional Inclusion}_i + \beta_2 \text{Digital Inclusion}_i + \xi_i$. v_i is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + v_i$ for the first and third columns and using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i$ for the second and fourth columns. We include fourth order polynomial in wealth, social status, religion, and the household's job type, and geographical location (village/ward). Additional controls include the number of household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category and the maximum age. The last two columns further include the sum of ages, and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, job type of the household, and geographic location of the household. Traditional inclusion is a dummy variable that takes the value 1 if the household (at least one member) has an account in a bank, post office, non-banking financial company (NBFC) or holds a credit card. Digital inclusion is a dummy variable that takes the value 1 if the household (at least one member) holds an E-Wallet.



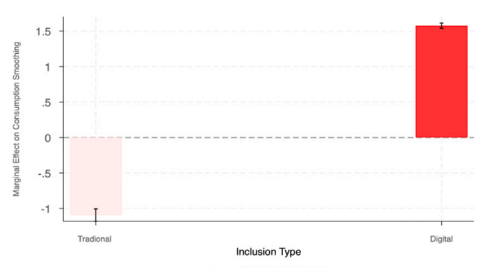
(a) Inclusion and Transitory Consumption



(b) Inclusion and Transitory Consumption



(c) Inclusion and Transitory Consumption



(d) Inclusion and Transitory Consumption

Fig. 8. The reported coefficients are from $\text{abs}v_i = \beta_0 + \beta_1 \text{Traditional Inclusion}_i + \beta_2 \text{Digital Inclusion}_i + \xi_i$. v_i is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + v_i$ for (a) and (c) and is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i$ for (b) and (d). We include fourth order polynomial in wealth, social status, religion, the household's job type, and geographical location (village/ward). Additional controls include the number of household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category and the maximum age. Figures (c) and (d) further include the sum of ages, and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, job type of the household, and geographic location of the household. Traditional inclusion is a dummy variable that takes the value 1 if the household (at least one member) has an account in a bank, post office, non-banking financial company (NBFC) or holds a credit card. Digital inclusion is a dummy variable that takes the value 1 if the household (at least one member) holds an E-Wallet.

different wealth quartiles. We have included the wealth quartile in the regression but have not shown it in Table 6, as that is not relevant to the discussion. As expected, the transitory consumption does not vary across wealth, as we estimate permanent consumption using a fourth-order polynomial in wealth and hence the transitory consumption is uncorrelated with wealth. As we see, digital inclusion is associated with higher transitory consumption at lower levels of wealth, and as wealth increases, the digital inclusion helps in lowering the transitory consumption. The coefficient of digital inclusion gives the effect at the first wealth quartile and the interactions give the incremental effect at other wealth quartiles. As we can see at the fourth wealth quartile, the coefficient becomes negative. This suggests an important role of liquidity constraints for households using digital inclusion at lower wealth quartiles. On the other hand, traditional inclusion is associated with lower

Table 6
Wealth, Inclusion, and Absolute Transitory Consumption.

	(1) Transitory Consumption	(2) Transitory Consumption
Digital Inclusion = 1	2.130***	1.733***
	(4.35)	(3.59)
Digital Inclusion = 1 × Quartile II of Wealth	−1.454*	−1.239*
	(−2.28)	(−1.97)
Digital Inclusion = 1 × Quartile III of Wealth	−1.854**	−1.462*
	(−3.18)	(−2.54)
Digital Inclusion = 1 × Quartile IV of Wealth	−2.376***	−2.054***
	(−4.23)	(−3.70)
Traditional Inclusion = 1	−1.340*	−1.326*
	(−1.99)	(−1.98)
Traditional Inclusion = 1 × Quartile II of Wealth	0.720	0.761
	(0.59)	(0.63)
Traditional Inclusion = 1 × Quartile III of Wealth	−0.691	−0.721
	(−0.50)	(−0.52)
Traditional Inclusion = 1 × Quartile IV of Wealth	1.159	1.090
	(0.56)	(0.53)
Observations	100,663	100,663

Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance level respectively. The reported coefficients are from $\text{abs}v_i = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{Wealth}_k \times \text{Digital Inclusion}_i + \sum_{k=1}^{n} \beta_2^k \text{Wealth}_k \times \text{Traditional Inclusion} + \xi_i$. v_i is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + v_i$ for the first column and $ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i$ for the second column. We include fourth order polynomial in wealth, social status, religion, and the household's job type, and geographical location (village/ward). Additional controls include the number of household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category, the maximum age, sum of ages, and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, job type of the household, and geographic location of the household. Traditional inclusion is a dummy variable that takes the value 1 if the household (at least one member) has an account in a bank, post office, non-banking financial company (NBFC) or holds a credit card. Digital inclusion is a dummy variable that takes the value 1 if the household (at least one member) holds an E-Wallet.

levels of transitory consumption at all levels of wealth and the effect does not vary across wealth levels.

Table 7 gives the marginal effect of digital inclusion on transitory consumption across different wealth quartiles from a model in which we include traditional inclusion to predict permanent consumption. This is added as a robustness, since it can be argued that consumption depends upon financial inclusion and hence in the absence of financial inclusion, the coefficient estimated from Eq. (6) to obtain the transitory consumption could be biased. The inclusion of traditional inclusion helps in capturing other unobserved factors, which could affect permanent consumption, and are related to digital inclusion. As we can see even if we include traditional inclusion to obtain transitory consumption, we find similar effects of digital inclusion across wealth quartiles. This suggests that transitory consumption is not likely to suffer from these unobservables which are correlated with consumption and inclusion. This is because traditional inclusion is the most important variable that could be correlated with digital inclusion and consumption, and the inclusion of this in the estimation of permanent consumption does not change the relationship between digital inclusion and transitory consumption.

5.4. Inclusion and asymmetric transitory consumption

The results presented in the previous section suggest that the digital inclusion is associated with higher transitory consumption at lower levels of wealth which is not the case with traditional inclusion. To explore this further, we estimate the relationship between negative and positive transitory consumption and measures of digital inclusion. The results presented in Table 8 suggest that included households experience lower negative transitory consumption. Further, the effect of traditional inclusion is stronger in the case of negative transitory consumption. In other words, the traditional inclusion serves as a better medium to cope with negative transitory shocks. Traditional inclusion does not influence positive transitory consumption, but digital inclusion leads to higher positive transitory consumption and this is the reason that digital inclusion leads to higher absolute transitory consumption. These results suggest that the digitally included households are more likely to experience positive transitory consumption. This is similar to the findings in Agarwal et al. (2019) which argue that digital payments lead to overspending by households.

To explore this further, we estimate the regression model for positive transitory consumption and inclusion measures at different wealth quartiles. These results are given in Table 9 and as we can see, the relationship between digital inclusion and positive transitory consumption is positive and significant at the first quartile of wealth. These households are most likely to face liquidity constraint and hence digital inclusion leads to overspending and a positive transitory component. As wealth increases, the positive transitory component decreases. This also helps us understand the relationship observed before between digital inclusion and transitory consumption in Tables 6 and 7 which show that at higher levels of wealth, digital inclusion is associated with lower transitory consumption. In the case of traditional inclusion, we do not observe any significant pattern between positive transitory consumption at different levels of wealth which is expected based on the relationship between traditional inclusion and positive transitory consumption as shown in Table 8.

5.5. Permanent and transitory consumption using counterfactual consumption

We construct a matched control group using the following variables: religion, sector, education category, occupation, social group, wealth, highest age, age of the household member with the highest education, sum of the ages of all household members, sum of the education years of all household members, and household size. Assuming financial inclusion does not affect permanent consumption, the difference between actual and counterfactual consumption reflects transitory consumption, Fig. 9. The before matching distribution shown in Fig. 9 is slightly different from the distribution shown in Fig. 1, because in Fig. 1, we use raw data, whereas in Figs. 9 and 10, we only use households having positive wealth, which is the estimation sample used in all previous regressions.

Table 7
Wealth, digital inclusion and absolute transitory consumption.

	(1) Transitory Consumption	(2) Transitory Consumption
Digital Inclusion = 1	2.065***	1.668***
	(4.23)	(3.46)
Digital Inclusion = 1 × Quartile II of Wealth	−1.398*	−1.182
	(−2.20)	(−1.88)
Digital Inclusion = 1 × Quartile III of Wealth	−1.801**	−1.411*
	(−3.09)	(−2.45)
Digital Inclusion = 1 × Quartile IV of Wealth	−2.307***	−1.986***
	(−4.11)	(−3.58)
Observations	100,663	100,663

Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance level respectively. The reported coefficients are from $\text{abs}v_i = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{Wealth}_k \times \text{Digital Inclusion}_i + \xi_i$. v_i is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + v_i$ for the first column and $ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i$ for the second column. We include fourth order polynomial in wealth, social status, religion, and the household's job type, as well as geographical location (village/ward). Additional controls include the number of household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category, the maximum age, the sum of ages, and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, job type of the household, and geographic location of the household. Digital inclusion is a dummy variable that takes the value 1 if the household (at least one member) holds an E-Wallet.

Table 8
Inclusion and asymmetric transitory consumption.

	(1) Transitory Component > 0	(2) Transitory Component < 0	(3) Transitory Component > 0	(4) Transitory Component < 0
Digital Inclusion	1.997***	1.654***	1.924***	1.767***
	(6.55)	(5.39)	(6.34)	(5.75)
Traditional Inclusion	−0.672	2.137**	−0.738	1.972*
	(−0.92)	(2.77)	(−1.02)	(2.54)
Observations	50,018	50,609	50,006	50,621

Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance level respectively. The reported coefficients are from $v_i = \beta_0 + \beta_1 \text{Traditional Inclusion}_i + \beta_2 \text{Digital Inclusion}_i + \xi_i$. v_i is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + v_i$ for the first and third columns and using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i$ for the second and fourth columns. We run separate regressions for v_i >0 and <0. We include fourth order polynomial in wealth, social status, religion, the household's job type, and geographical location (village/ward). Additional controls include the number of household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category and the maximum age. The last two columns further include the sum of ages, and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, job type of the household, and geographic location of the household. Traditional inclusion is a dummy that takes the value 1 if the household (at least one member) has an account in a bank, post office, non-banking financial company (NBFC) or holds a credit card. Digital inclusion is a dummy that takes the value 1 if the household (at least one member) holds an E-Wallet.

We can see the accuracy of the matching by observing the covariates' distribution before and after matching. As we can see from Figs. 10 and 11, the nearest neighbor does a good job and provides perfect matching over covariates (education and social group) for households with (treated) and without (control) digital financial inclusion. Appendix D gives the graphs related to covariate matching for other variables, which illustrate the robustness of this approach in matching. As we can see from Fig. 9, the existing difference between the consumption of households having and not having digital financial inclusion goes down after matching, but still persists. We believe that since the households are identical in all aspects, the difference in consumption is primarily transitory consumption driven by digital inclusion. It is hard to believe that just digital inclusion, conditional on everything else being the same, would give rise to higher permanent consumption. It is also hard to argue that these differences are driven by differential shocks affecting these households.

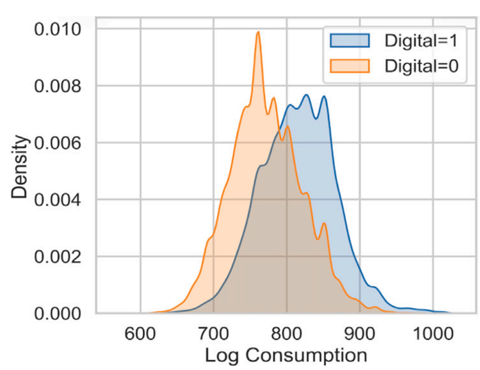
This matching-based estimate gives higher estimates of transitory consumption compared to regression based estimates reported before. The absolute value of transitory consumption (absolute value of the difference between actual and counterfactual consumption) for digital financial inclusion is 54.208 (Table 10), which is higher than the effect shown in Table 5, but qualitatively the same.[12] Further, we include traditional inclusion and village/ward for matching. This is a very extensive matching as we match people across the same characteristics in the same village/ward, and also on traditional inclusion. These results are also similar to previous results and are given in Fig. 12. With this extensive matching, we find that the transitory consumption associated with digital financial inclusion is 54.203 (Table 10). It is hard to argue that, conditional on the same traditional inclusion and everything else, access to digital inclusion would lead to higher permanent consumption.

[12] These effects are higher than estimates of transitory consumption due to digital inclusion in Table 5, but this is not directly comparable as it is from a smaller sample. Also it is important to mention that these are not differences in consumption but transitory consumption. But we also find that even after balancing on all these important determinants the households with digital inclusion have 8% higher per-capita consumption compared to households without digital inclusion and hence these transitory consumptions are mostly driven by higher consumption.

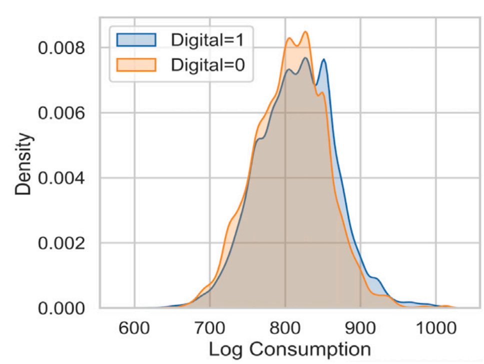
Table 9
Inclusion, wealth and asymmetric transitory consumption.

	(1) Transitory Component > 0	(2) Transitory Component > 0
Digital Inclusion = 1	5.984***	5.474***
	(8.79)	(8.16)
Digital Inclusion = 1 × Quartile II of Wealth	−2.367**	−1.901*
	(−2.59)	(−2.11)
Digital Inclusion = 1 × Quartile III of Wealth	−4.786***	−4.212***
	(−5.75)	(−5.13)
Digital Inclusion = 1 × Quartile IV of Wealth	−5.577***	−5.075***
	(−7.06)	(−6.49)
Traditional Inclusion Inclusion = 1	−0.876	−0.788
	(−0.93)	(−0.85)
Traditional Inclusion Inclusion = 1 × Quartile II of Wealth	1.583	0.621
	(0.90)	(0.36)
Traditional Inclusion Inclusion = 1 × Quartile III of Wealth	1.209	1.166
	(0.61)	(0.60)
Traditional Inclusion Inclusion = 1 × Quartile IV of Wealth	1.515	2.132
	(0.51)	(0.72)
Observations	50,018	50,006

Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance level respectively. The reported coefficients are from $v_i < 0 = \beta_0 + \beta_1 \text{Traditional Inclusion}_i + \beta_2 \text{Digital Inclusion}_i + \xi_i$. v_i is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + v_i$ for the first column and $ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i$ for the second column. We include fourth order polynomial in wealth, social status, religion, and the household's job type, as well as geographical location (village/ward). Additional controls include the number of household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category, the maximum age, the sum of ages, and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, job type of the household, and geographic location of the household. Traditional inclusion is a dummy variable that takes the value 1 if the household (at least one member) has an account in a bank, post office, non-banking financial company (NBFC) or holds a credit card. Digital inclusion is a dummy variable that takes the value 1 if the household (at least one member) holds an E-Wallet.



(a) Log Consumption: Before Matching



(b) Log Consumption: After Matching

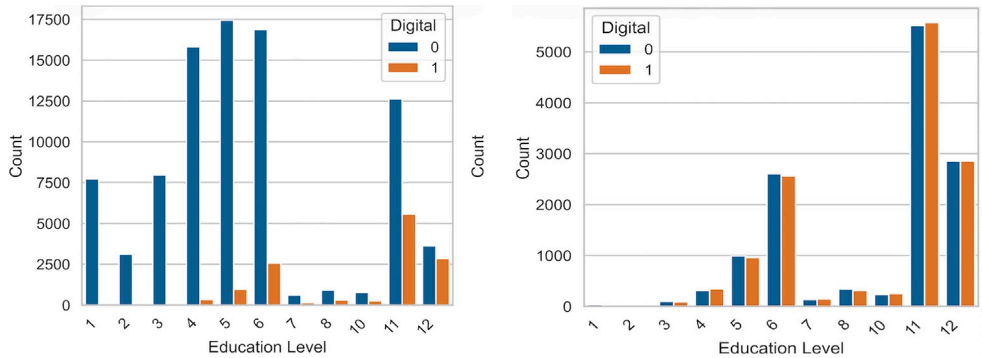
Fig. 9. Log consumption before and after matching. We match households using religion, sector, education category, occupation, social group, wealth, highest age, age of the household member with the highest education, sum of the ages of all household members, sum of the education years of all household members, and size of the household.

Comparing these two results, we can also argue that the omission of traditional inclusion in the regression-based estimates is not likely to cause significant variation in the estimates of permanent consumption used above.

5.6. Digital Inclusion and transitory consumption: instrumental variable regression

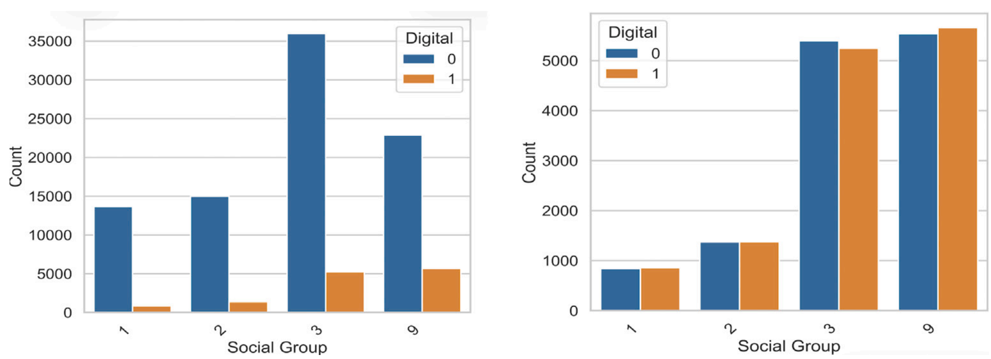
The counterfactual estimator in the previous section provides overwhelming evidence that digital inclusion is associated with higher transitory consumption. Although we match using traditional inclusion to arrive at the above conclusion, the matching is only on observables and the main threats are unobservables. A large literature has used the availability of financial services as an instrumental variable for financial inclusion, arguing that these are unlikely to be related to the household level unobserved factors which influence consumption decisions. Riley (2018) and Barry and Creti (2023) use the availability of mobile money services in each village/ward as an instrumental variable to estimate the effect of financial inclusion. As mentioned above, the measure of digital inclusion used in this paper is the same/similar to mobile money services used in Riley (2018) and Barry and Creti (2023).

Following these studies, we use the proportion of households that use digital financial services (excluding the nodal household), as an instrumental variable for digital financial inclusion. A higher proportion of digitally included households captures the exogenous supply of digital financial inclusion which could be driven by the availability of such



(a) Education: Before Matching (b) Education: After Matching

Fig. 10. Education levels before and after matching. We match households using religion, sector, education category, occupation, social group, wealth, highest age, age of the household member with the highest education, sum of the ages of all household members, sum of the education years of all household members, and size of the household.



(a) Social Group (Caste): Before Matching (b) Social Group (Caste): After Matching

Fig. 11. Social group (caste) level before and after matching. We match households using religion, sector, education category, occupation, social group, wealth, highest age, age of the household member with the highest education, sum of the ages of all household members, sum of the education years of all household members, and size of the household.

Table 10
Transitory consumption and digital inclusion.

	Model 1 Absolute Transitory Consumption	Model 2 Absolute Transitory Consumption
Digital Inclusion	54.208	54.203
Number of Observations	26,290	26,290

Notes: Model 1 is with counterfactual (permanent) consumption obtained by matching households using, religion, sector, job type, household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category, the maximum age, sum of ages, and the total years of education of all household members aged 14 years or older. Model 2 has traditional inclusion and village/ward as additional matching variables to obtain counterfactual (permanent) consumption. The difference between consumption and permanent consumption gives transitory consumption.

services. We use this as an instrumental variable for digital financial inclusion. The intuition is that, if in a village a large proportion of people are digitally included that captures the availability of such services and increases the probability of a household being digitally included. Since we exclude the household considered in obtaining the proportion, the variation being used to predict household digital inclusion is exogenous to the household and unrelated to the household consumption decisions.

Table 11 presents the results which are the same as Table 5 except that we use the instrumental variable for digital financial inclusion. The Kleibergen-Paap rk Wald F statistic suggests that the instrument is strong. Further the Durbin-Wu-Hausman statistics suggest that OLS estimates are not consistent and hence the instrumental variable strategy is required in this case. The instrumental variable regression gives an even higher effect of digital financial inclusion on transitory consumption. We estimate an additional model in which we include the traditional inclusion in the estimation of the unobserved permanent consumption (Table 12) and these results are also similar to the results reported in Table 11. These results suggest that digital inclusion is associated with higher transitory consumption.[13]

[13] We also estimate a model of consumption where we use the same instrumental variable for digital inclusion and these results give an overwhelming response that digital inclusion is associated with higher consumption. Most importantly these estimates are quantitatively similar to the estimates given by the counterfactual estimator in the previous section and are provided in Appendix E of the paper.

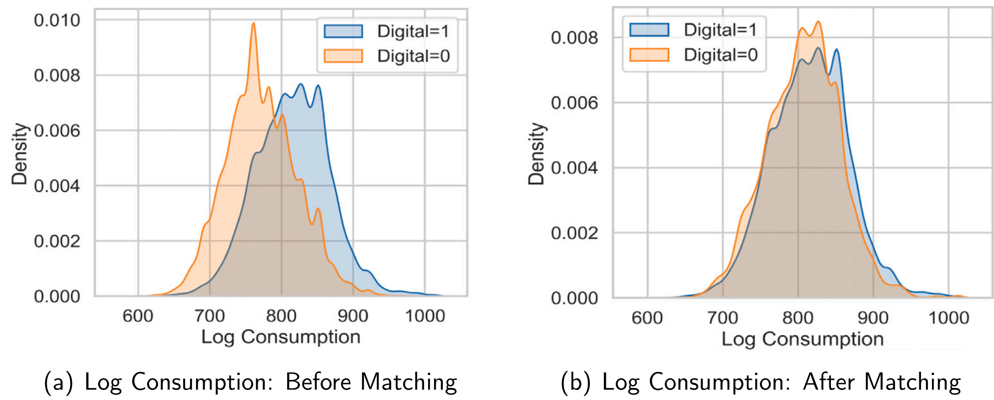


Fig. 12. Log consumption before and after matching. We match households using, religion, sector, education category, occupation, social group, wealth, highest age, age of the household member having the highest education, sum of the ages of all household members, sum of education years of all household members, size of the household, traditional inclusion and village/ward of the household.

Table 11
Inclusion and Absolute Transitory Consumption: Instrumental Variable Regression.

	(1) Transitory Consumption	(2) Transitory Consumption	(3) Transitory Consumption	(4) Transitory Consumption
Digital Inclusion	5.963***	5.775***	6.111***	5.856***
	(9.36)	(9.20)	(9.52)	(9.30)
Traditional Inclusion	−1.793***	−1.728**	−1.764***	−1.679**
	(−3.38)	(−3.25)	(−3.33)	(−3.17)
Village Fixed Effects	Yes	Yes	Yes	Yes
Observations	100,663	100,663	100,663	100,663
Kleibergen-Paap rk Wald F statistic	16,597.2	16,597.2	16,597.2	16,597.2
First Stage t Statistics	146.17	146.17	146.17	146.17
Durbin-Wu-Hausman	0.000	0.000	0.000	0.000

Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance level respectively. The reported coefficients are from $\text{abs}v_i = \beta_0 + \beta_1\text{Traditional Inclusion}_i + \beta_2\text{Digital Inclusion}_i + \xi_i$. v_i is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + v_i$ for the first and third columns and using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i$ for the second and fourth columns. We use village level digital inclusion intensity as an instrumental variable for household digital inclusion. We include fourth order polynomial in wealth, social status, religion, the household's job type, and geographical location (village/ward). Additional controls include the number of household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category and the maximum age. The last two columns further include the sum of ages, and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, the job type of the household, and the geographic location of the household. Traditional inclusion is a dummy variable that takes the value 1 if the household (at least one member) has an account in a bank, post office, non-banking financial company (NBFC) or holds a credit card. Digital inclusion is a dummy variable that takes the value 1 if the household (at least one member) holds an E-Wallet.

Table 12
Inclusion and Absolute Transitory Consumption: Instrumental Variable Regression.

	(1) Transitory Consumption	(2) Transitory Consumption	(3) Transitory Consumption	(4) Transitory Consumption
Digital Inclusion	5.910***	5.721***	6.057***	5.803***
	(9.29)	(9.14)	(9.46)	(9.24)
Village Fixed Effects	Yes	Yes	Yes	Yes
Observations	100,663	100,663	100,663	100,663
Kleibergen-Paap rk Wald F statistic	16,662.7	16,662.7	16,662.7	16,662.7
First Stage t Statistics	146.17	146.17	146.17	146.17
Durbin-Wu-Hausman	0.000	0.000	0.000	0.000

Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance level respectively. The reported coefficients are from $\text{abs}v_i = \beta_0 + \beta_1\text{Traditional Inclusion}_i + \beta_2\text{Digital Inclusion}_i + \xi_i$. v_i is obtained using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + v_i$ for the first and third columns and using $ln\left(c_i\right) = Z_i\gamma + c(A_i) + \alpha IMR_i + v_i$ for the second and fourth columns. We use village level digital inclusion intensity as an instrumental variable for household digital inclusion. We include fourth order polynomial in wealth, social status, religion, the household's job type, and geographical location (village/ward). Additional controls include the number of household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category and the maximum age. The last two columns further include the sum of ages, and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, job type of the household, and geographic location of the household. Digital inclusion is a dummy variable that takes the value 1 if the household (at least one member) holds an E-Wallet.

Table 13
Financial Inclusion and borrowing Cost

	(1) Interest Rate	(2) Interest Rate
Digital Inclusion	−0.332*	−0.230*
	(−2.40)	(−2.00)
Traditional Inclusion	−2.428***	−0.817*
	(−5.12)	(−2.05)
Wealth (100,000 Rupee)	−0.00181***	−0.00167***
	(−6.15)	(−6.84)
Borrowing (100,00 Rupee)	−0.0139*	−0.00643
	(−2.03)	(−1.13)
Block Fixed Effects	Yes	Yes
Religion Fixed Effects	Yes	Yes
Social Status Fixed Effects	Yes	Yes
Education Fixed Effects	Yes	Yes
Observations	106,029	105,271

Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance levels respectively. β_1, β_2, β_3, β_4 from $\text{Borrowing Rate}_{ij}) = \beta_0 + \beta_1\text{Traditional Inclusion}_i + \beta_2\text{Digital Inclusion}_i + \beta_3\text{Wealth}_i + \beta_4\text{Borrowing}_i + \text{Social Status}_i + \text{Religion}_i + \text{Education}_i + \text{Village/Ward}_j + e_{ij}$. Traditional inclusion is a dummy variable that takes the value 1 if the household (at least one member) has an account in a bank, post office, non-banking financial company (NBFC) or holds a credit card. Digital inclusion is a dummy variable that takes the value 1 if the household (at least one member) holds an E-Wallet. The left column represents the actual rate of borrowing and the right panel represents the rate of borrowing winsorized at 5%. Wealth is the sum of the values of land and buildings, livestock, transport equipment, farm and non-farm equipment deposits minus loans of the household.

5.7. Financial inclusion and cost of borrowing

Results presented in Table 8 suggest that both traditional and digital inclusion are associated with lower negative transitory consumption for households and the effect of traditional inclusion is more pronounced. There are many channels through which financial inclusion can lead to consumption smoothing. Households can accumulate assets to smooth consumption and improve their well-being as argued in Chipunza and Fanta (2024). Also the households can use borrowings to smooth negative transitory consumption. Results presented in the previous section suggest that traditional inclusion may be enabling households to borrow at better terms and hence, is associated with lower negative transitory consumption compared to digital inclusion. We test this using a regression in which the dependent variable is the borrowing cost. The regression model is estimated using the loan level data for households available in the survey. Table 13 presents the results for the borrowing cost model. We estimate two models: the column 1 is with all observations on borrowings and corresponding interest rates, and column 2 is with the rate of borrowing winsorized at 5% in both the tails. We winsorize the borrowings as there are zeros as well as very high values of borrowing cost in the data. As we can see, traditional inclusion leads to a lowering of borrowing cost by 0.8 to 2.4% whereas digital inclusion reduces the borrowing costs by 0.23 to 0.33%. This is important as the earlier results suggest that the marginal effect of traditional inclusion on consumption smoothing is stronger than that of digital inclusion. This makes sense as the marginal effect of traditional inclusion on borrowing cost is much higher compared to digital inclusion. The coefficient of wealth is very similar in these two columns, and it is negative and significant.

6. Concluding remarks and policy implications

We estimated the effect of traditional and digital financial inclusion on transitory consumption using nationally representative survey data from India. We find significant heterogeneity in the relationship between these two inclusion measures and transitory consumption. Traditional inclusion is associated with lower transitory consumption on average, whereas digital inclusion is associated with higher transitory consumption. We also find that both traditional and digital inclusion lower the borrowing cost, but the marginal effect of traditional inclusion on the borrowing cost is much higher compared to digital inclusion. This explains the differences in the marginal effect of traditional and digital inclusion in ensuring consumption smoothing. These regression results suggest that wealth is an important determinant of the borrowing cost and hence at a higher level of wealth, the borrowing costs are low enough for households to smooth consumption. These results together explain why the effectiveness of financial inclusion in consumption smoothing increases with wealth.

The over-sensitivity of consumption due to digital inclusion has also been argued in Agarwal et al. (2019) and Lai et al. (2020). This also corroborates the findings of Pellegrino et al. (2022) that digital inclusion, in particular, can lead to impulsive buying behaviors through various digital platforms. The impulsive consumption due to digital financial inclusion has important policy implications. Policymakers must ensure that fintech-driven digital inclusion promotes equitable access to credit markets while safeguarding households from falling into debt traps caused by predatory or unfair lending practices. Additionally, educational programs on responsible digital financial management should be developed to help households navigate digital tools effectively, minimizing impulsive spending and fostering long-term financial stability.

CRediT authorship contribution statement

Abhishek Kumar: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Sushanta Mallick:** Writing – review & editing, Writing – original draft, Resources, Project administration, Investigation, Formal analysis, Conceptualization. **Apra Sinha:** Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Financial inclusion and well-being: State level evidence

The traditional measure of the Human Development Index (HDI) consists of three factors: life expectancy, school enrollment and GDP per capita. In the first stage we construct individual indices as per the standard methodology and then take arithmetic and geometric averages to obtain the combined HDI as explained below. Fig. A.1 gives the relationship between HDI and GDP per capita for major Indian states in 2019. The Spearman rank correlation is 0.80 and is statistically significant, which suggests a significant relationship between per-capita income and HDI.

Then we create two further measures of well being by including traditional and digital inclusion in the HDI obtained from household survey data. We observe the status of individual-level financial inclusion and code them into included or not included. Using these dummies and the weights provided in the survey, we construct the proportion of traditionally and digitally included people in each state which is used to construct well-being indices. In the first measure we only include the traditional financial inclusion, and the well-being measure is given by:

$$\text{WellBeingI} = (\text{GDP Per Capita Index} \times \text{Enrollment} \times \text{Life Expectancy Index} \times \text{Traditional Financial Inclusion})^{1/4}$$

In the second well-being measure, we include the average of traditional and digital financial inclusion as a measure of financial inclusion which is given by:

$$\text{WellBeingII} = (\text{GDP Per Capita Index} \times \text{Enrollment} \times \text{Life Expectancy Index} \times \text{Financial Inclusion})^{1/4}$$

Fig. A.2 gives these two measures of well-being. As we can see, the correlation between these two measures of well-being and the GDP index is strong. The strong positive correlation between well-being indices including financial inclusion could arise due to the nexus between growth and financial development, which has been documented in the literature. King and Levine (1993a) using a panel of countries argue that financial development predicts future growth.

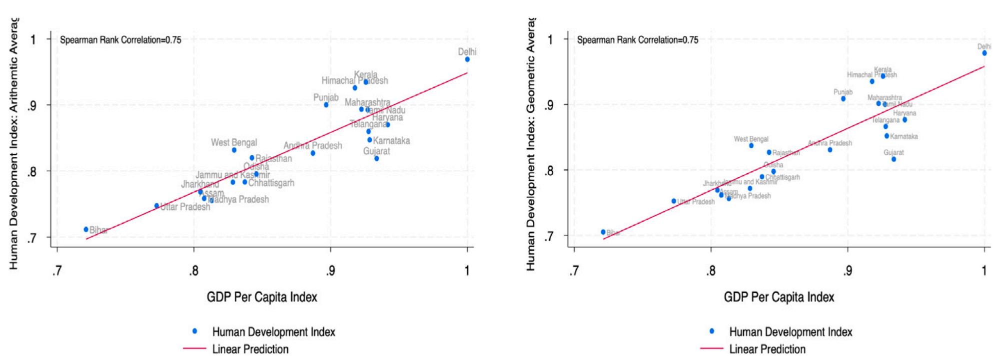
Appendix B. Further insights from data

See Table B.1 and Figs. B.2–B.7.

Table B.1
Borrowing from Different Agencies.

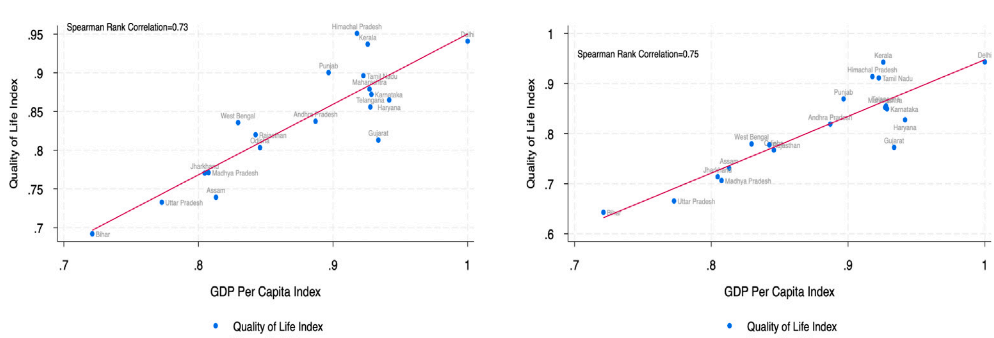
S.No	Agency	% Observations
1	Scheduled commercial bank	29.6
2	Regional rural bank	3.7
3	Co-operative society	4.6
4	Co-operative bank	2.7
5	Insurance companies	0.3
6	Provident fund	0.1
7	Employer	0.1
8	Financial corporation/institution	5.80
9	NBFC's including micro-financing institution(MFIs)	5.1
10	Bank linked SHG/JLG	7.7
11	Non-bank linked SHG/JLG	1.2
12	Other institutional agencies	1.0
13	Landlord	1.0
14	Agricultural moneylender	3.1
15	Professional moneylender	14.7
16	Input supplier	0.6
17	Relatives and friends	17.5
18	Chit fund	0.4
19	Market commission agent/traders	0.7

Notes: The original data contain 20 categories, but we combined two of them, 8 and 9, which is serial number 8th in Table B.1.



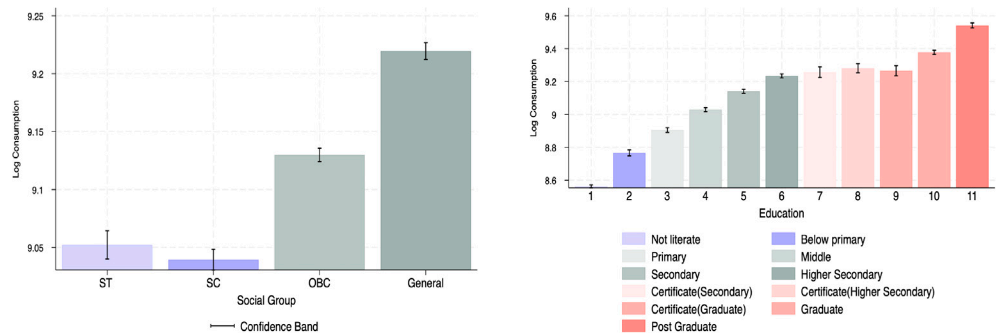
(a) HDI Arithmetic (b) HDI Geometric

Fig. A.1. Human Development Indices.



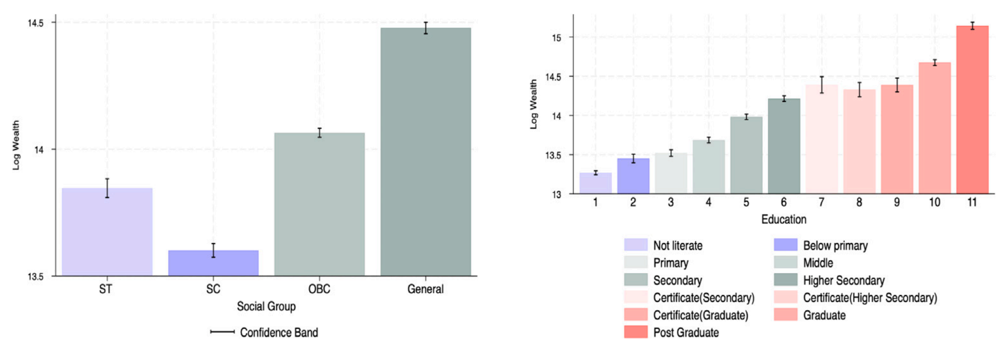
(a) Well Being Index I (b) Well Being Index II

Fig. A.2. Well-being measures including traditional and digital financial inclusion.



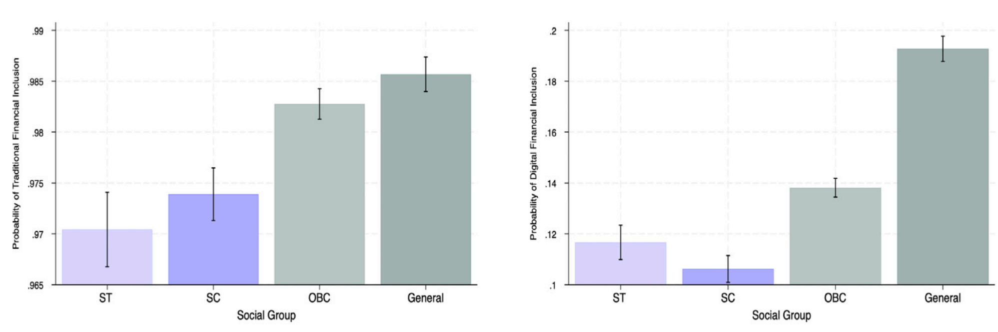
(a) Social Group and Consumption (b) Education and Consumption

Fig. B.1. Social group and consumption, education and consumption (a) represents β_0 and β_1^k from $\text{Log Consumption}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Social Status}_k + \theta_j + e_{ij}$ (b) represents β_0 and β_1^k from $\text{Log Consumption}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Education}_k + \theta_j + e_{ij}$. θ_j is village fixed effects.



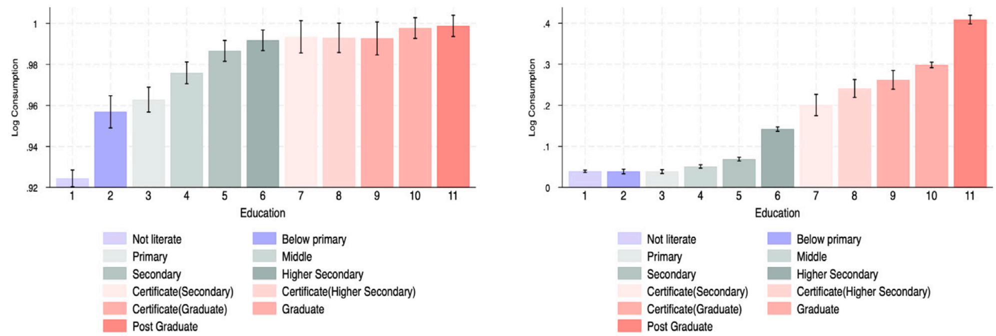
(a) Social Status and Wealth (b) Education and Wealth

Fig. B.2. Social Status, education and wealth (a) β_0 and β_1^k from $\text{Log Wealth}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Social Status}_k + \theta_j + e_{ij}$ (b) β_0 and β_1^k from $\text{Log Wealth}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Education}_k + \theta_j + e_{ij}$. Wealth is the sum of the values of land and buildings, livestock, transport equipment, farm and non-farm equipment deposits minus loans of the household. θ_j is village fixed effects.



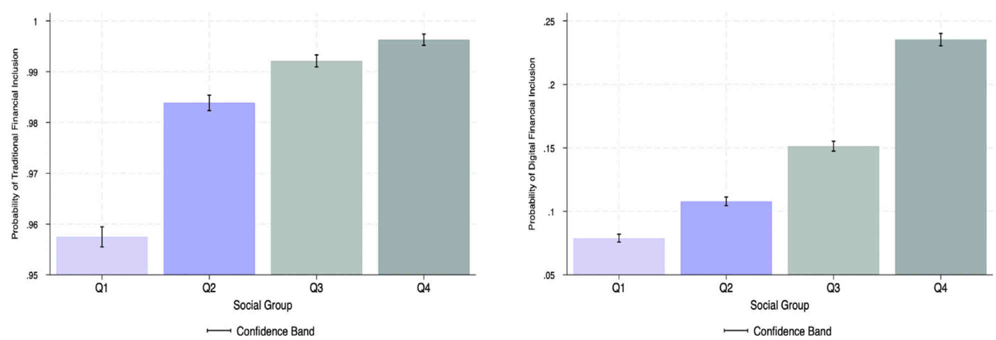
(a) Probability: Traditional Inclusion (b) Probability: Digital Inclusion

Fig. B.3. Social status and financial inclusion (a) β_0 and β_1^k from $\text{Traditional inclusion Dummy}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Social Status}_k + \theta_j + e_{ij}$ (b) β_0 and β_1^k from $\text{Digital inclusion Dummy}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Social Status}_k + \theta_j + e_{ij}$. The traditional inclusion dummy takes the value 1 if the household (at least one member) has an account in a bank, post office or non-banking financial company (NBFC) or holds a credit card. The digital inclusion dummy takes the value 1 if the household (at least one member) holds an E-Wallet. θ_j is village fixed effects.



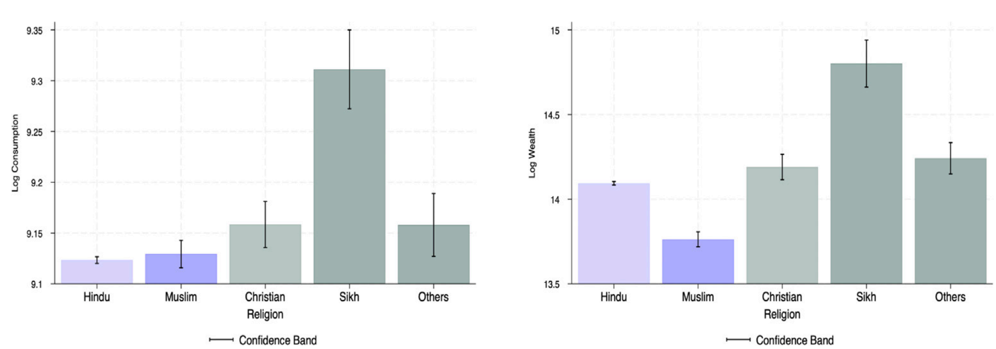
(a) Probability: Traditional Inclusion (b) Probability: Digital Inclusion

Fig. B.4. Education and financial inclusion (a) β_0 and β_1^k from $\text{Traditional inclusion Dummy}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Education}_k + \theta_j + e_{ij}$ (b) β_0 and β_1^k from $\text{Digital inclusion Dummy}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Education}_k + \theta_j + e_{ij}$. θ_j is village fixed effects. The traditional inclusion dummy takes the value 1 if the household (at least one member) has an account in a bank, post office or non-banking financial company (NBFC) or holds a credit card. The digital inclusion dummy takes the value 1 if the household (at least one member) holds an E-Wallet.



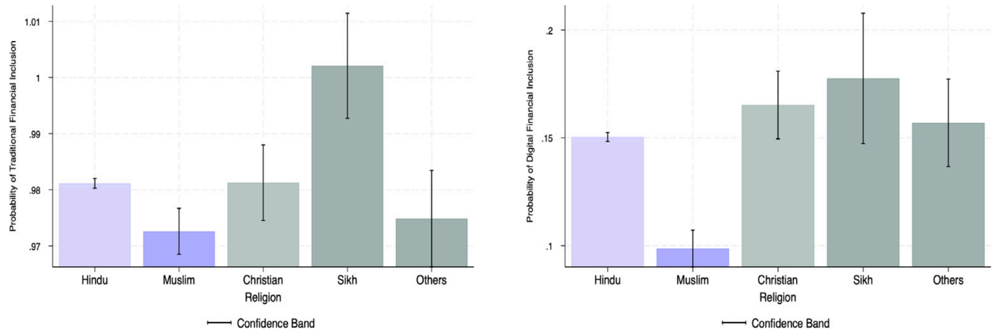
(a) Probability: Traditional Inclusion (b) Probability: Digital Inclusion

Fig. B.5. Wealth and financial inclusion (a) β_0 and β_1^k from $\text{Traditional inclusion Dummy}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Wealth}_k + \theta_j + e_{ij}$ (b) β_0 and β_1^k from $\text{Digital inclusion Dummy}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Wealth}_k + \theta_j + e_{ij}$. θ_j is village fixed effects. The traditional inclusion dummy takes the value 1 if the household (at least one member) has an account in a bank, post office or non-banking financial company (NBFC) or holds a credit card. The digital inclusion dummy takes the value 1 if the household (at least one member) holds an E-Wallet. Wealth is the sum of the values of land and buildings, livestock, transport equipment, farm and non-farm equipment and deposits minus loans of the household.



(a) Religion and Consumption (b) Religion and Wealth

Fig. B.6. Religion and consumption (a) is β_0 and β_1^k from $\text{Log Consumption}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Religion}_k + \theta_j + e_{ij}$ (b) is β_0 and β_1^k from $\text{Log Wealth}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k \text{ Religion}_k + \theta_j + e_{ij}$. θ_j is village fixed effects. Wealth is the sum of the values of land and buildings, livestock, transport equipment, farm and non-farm equipment deposits minus loans of the household.



(a) Probability: Traditional Inclusion (b) Probability: Digital Inclusion

Fig. B.7. Religion and financial inclusion β_0 and β_1^k from $\text{Inclusion Dummy}_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_1^k\ \text{Religion}_k + \theta_j + e_{ij}$. θ_j is village fixed effects. The traditional inclusion dummy takes the value 1 if the household (at least one member) has an account in a bank, post office or non-banking financial company (NBFC) or holds a credit card. The digital inclusion dummy takes the value 1 if the household (at least one member) holds an E-Wallet.

Appendix C. Is transitory consumption reliable? additional results

Table C.1
Borrowing for legal emergency and transitory consumption.

	(1) Absolute Transitory Component	(2) Absolute Transitory Component
Constrained Households	8.028	8.035
	(1.11)	(1.11)
Observations	100,663	100,663

Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance level respectively. Constrained is the coefficient of constrained households from $\text{abs}\nu_i = \beta_0 + \beta_i\ \text{Constrained} + \xi_i$. ν_i for the first column is derived using $ln\left(c_i\right) = Z_i\gamma - c(A_i) + \nu_i$ and for the second column it is derived using $ln\left(c_i\right) = Z_i\gamma - c(A_i) + \alpha IMR_i + \nu_i$. We include the social status, religion, education category, sum of years of education of all the members of the household, age of the oldest person in the household, age of the person with the highest level of education, sum of the ages of all the household members, geographical location of the household (village/ward), fourth order polynomial in wealth and the job type of the household. IMR_i is the inverse Mills ratio which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, sum of years of education of all the members of the household, age of the oldest person in the household, age of the person with the highest level of education, sum of the ages of all the household members, and job type of the household.

Appendix D. Transitory consumption using counterfactual consumption: propensity score matching

See Figs. D.1–D.9.

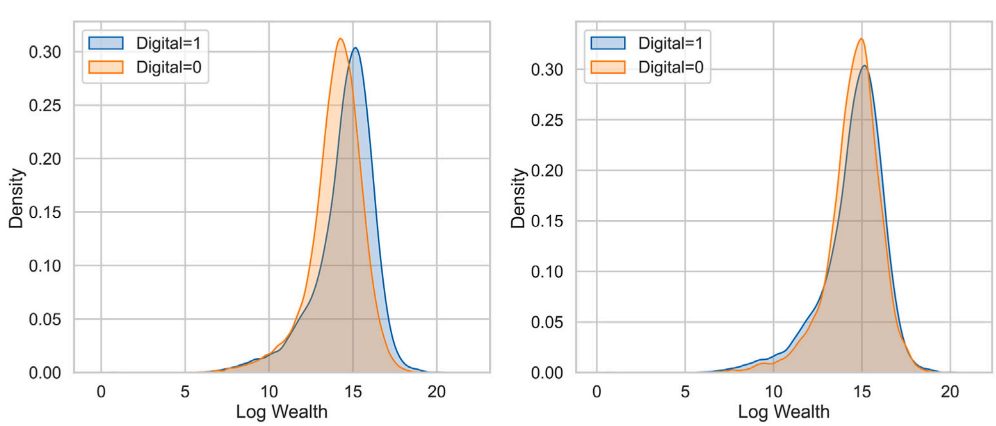


Fig. D.1. Log wealth before and after matching. We match households using, religion, sector, education category, occupation, social group, wealth, highest age, age of the household member with the highest education, sum of the ages of all household members, sum of the education years of all household members, and size of the household.

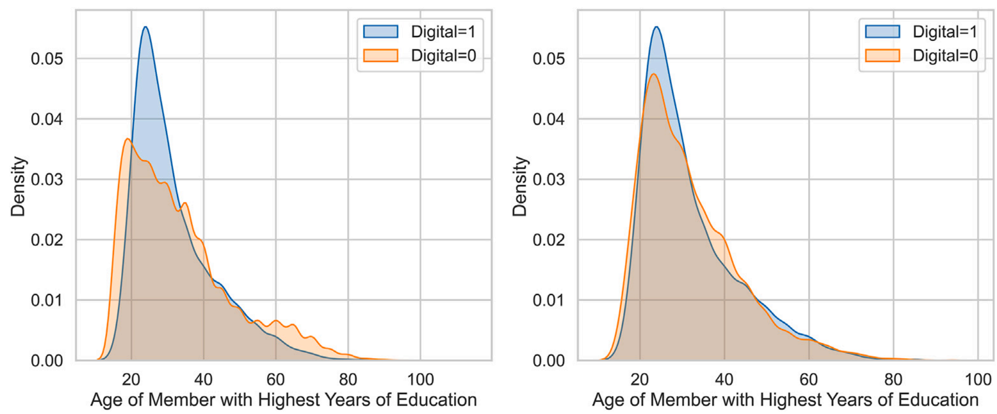


Fig. D.2. Age of the household member with the highest years of education before and after matching. We match households using, religion, sector, education category, occupation, social group, wealth, highest age, age of the household member with the highest education, sum of the ages of all household members, sum of the education years of all household members, and size of the household.

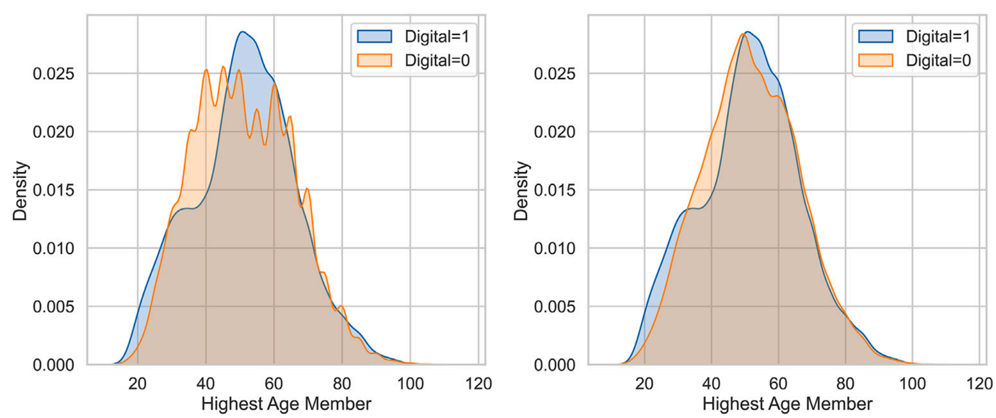


Fig. D.3. Highest age of the household member before and after matching. We match households using, religion, sector, education category, occupation, social group, wealth, highest age, age of the household member with the highest education, sum of the ages of all household members, sum of education years of all household members, and size of the household.

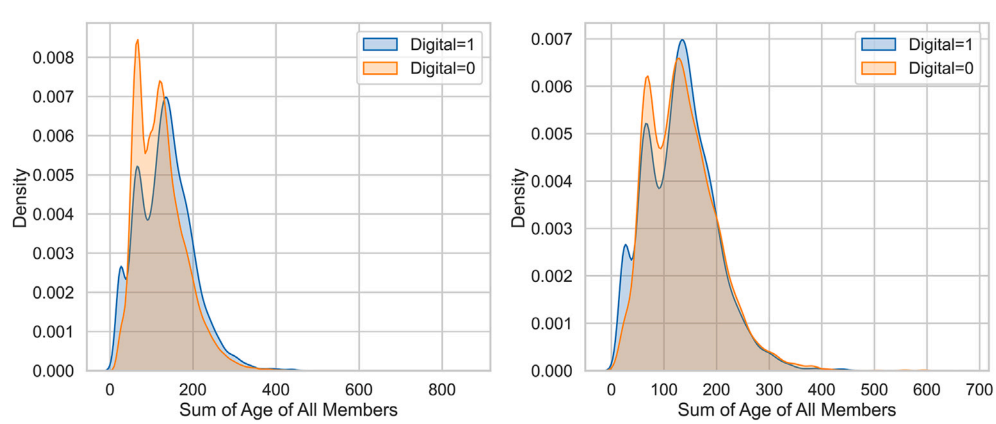


Fig. D.4. Sum of the ages of the household members with the highest years of education before and after matching. We match households using, religion, sector, education category, occupation, social group, wealth, highest age, age of the household member with the highest education, sum of the ages of all household members, sum of the education years of all household members, and size of the household.

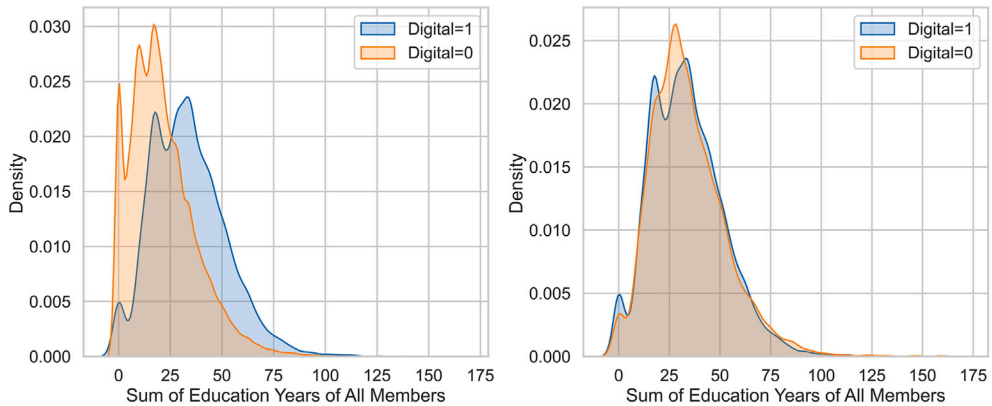


Fig. D.5. Sum of education years of the household members before and after matching. We match households using, religion, sector, education category, occupation, social group, wealth, highest age, age of the household member with the highest education, sum of the ages of all household members, sum of the education years of all household members, and size of the household.

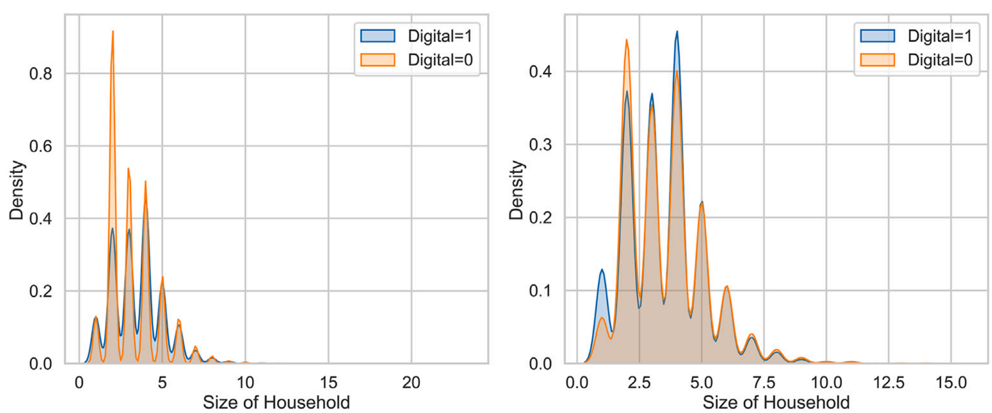


Fig. D.6. Size of the household before and after matching. We match households using, religion, sector, education category, occupation, social group, wealth, highest age, age of the household member having the highest education, sum of the ages of all household members, sum of education years of all household members, and size of the household.

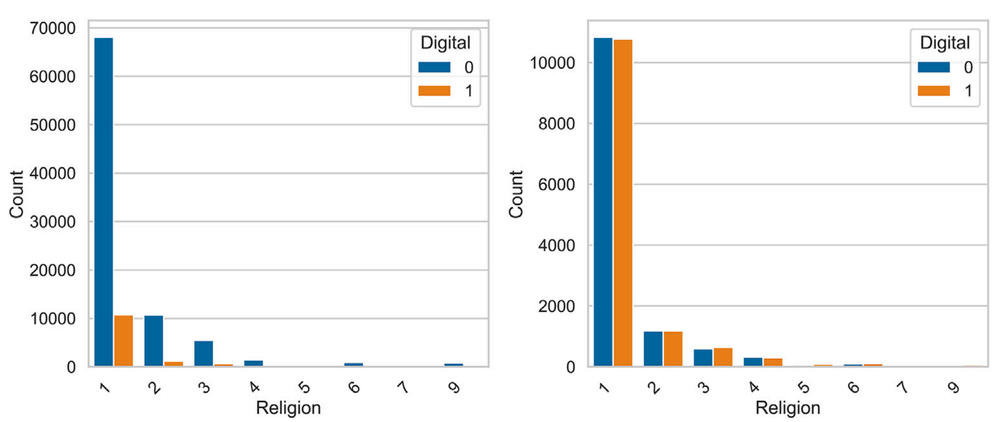


Fig. D.7. Religion of the household before and after matching. We match households using, religion, sector, education category, occupation, social group, wealth, highest age, age of the household member having the highest education, sum of the ages of all household members, sum of education years of all household members, and size of the household.

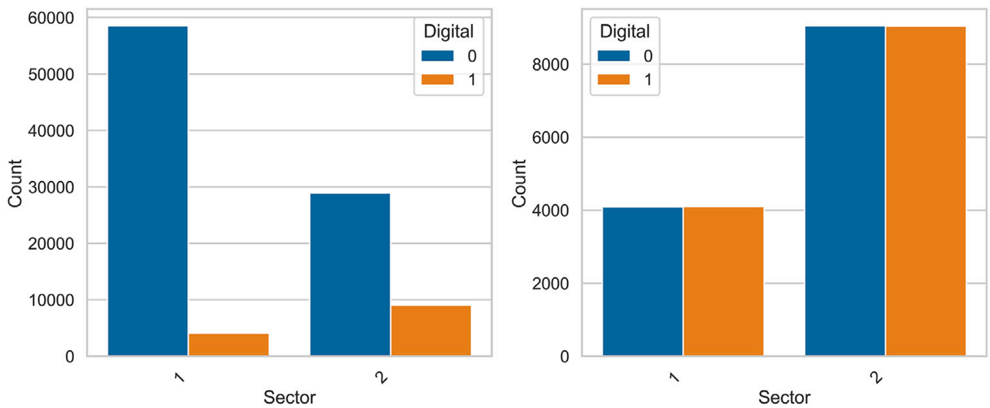


Fig. D.8. Sector of the household before and after matching. We match households using, religion, sector, education category, occupation, social group, wealth, highest age, age of the household member having the highest education, sum of the ages of all household members, sum of the education years of all household members, and size of the household.

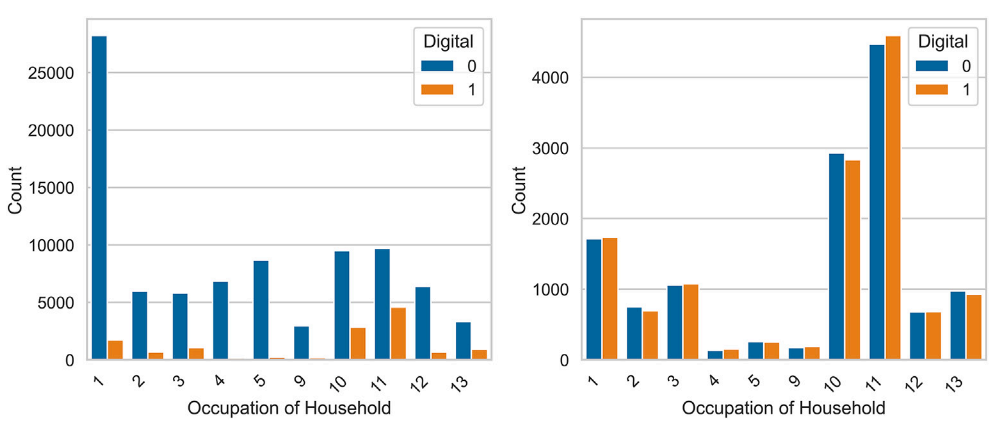


Fig. D.9. Occupation of the household before and after matching. We match households using, religion, sector, education category, occupation, social group, wealth, highest age, age of the household member having the highest education, sum of the ages of all household members, sum of education years of all household members, and size of the household.

Appendix E. IV regression: additional results

See Table E.1.

Table E.1
Financial Inclusion and Consumption.

	(1) Log Consumption	(2) Log Consumption	(3) Log Consumption	(4) Log Consumption
Digital Inclusion	9.002***	8.995***	9.137***	9.149***
	(21.06)	(21.18)	(21.40)	(21.58)
Traditional Inclusion	2.449*	2.546*	2.526*	2.649**
	(2.44)	(2.55)	(2.52)	(2.66)
Village Fixed Effects	Yes	Yes	Yes	Yes
Observations	100,627	100,627	100,627	100,627
Kleibergen-Paap rk Wald F statistic	21,753.2	21,753.7	21,739.6	21,740.8

Notes: *, **, and *** denote significance at 5%, 1%, and.1% significance level respectively. The reported coefficients are from $\text{Log Consumption} = \beta_0 + \beta_1 \text{ Traditional Inclusion}_i + \beta_2 \text{ Digital Inclusion}_i + Z_i\gamma + c(A_i) + e_i$ in columns (1) and (3) and $\text{Log Consumption} = \beta_0 + \beta_1 \text{ Traditional Inclusion}_i + \beta_2 \text{ Digital Inclusion}_i + Z_i\gamma + c(A_i) + \delta IMR_i + e_i$ in columns (2) and (4). We use village level digital inclusion intensity as an instrumental variable for households digital inclusion. We include fourth order polynomial in wealth, social status, religion, the household's job type, and geographical location (village/ward). Additional controls include the number of household members aged 14 years or older, the highest education category among them, the age of the household member with the highest education category and the maximum age. The last two columns further include the sum of ages, and the total years of education of all household members aged 14 years or older. IMR_i is the inverse Mills ratio, which is obtained from a probit model for observing wealth greater than 0 using social status, religion, education category, age of the oldest person in the household, age of the person having the highest level of education, job type of the household, and geographic location of the household. Traditional inclusion is a dummy variable that takes the value 1 if the household (at least one member) has an account in a bank, post office, non-banking financial company (NBFC) or holds a credit card. Digital inclusion is a dummy variable that takes the value 1 if the household (at least one member) holds an E-Wallet.

Data availability

Data will be made available on request.

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