Digital Finance and Structural Change in Labor: A Gendered Perspective*

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Abstract

This paper evaluates the gender-specific effects of digital financial services (DFS) on labor market participation, focusing on occupational change, and the intensity of employment margins measured using time-use data. Using multiple nationally representative data sets from India, and a two-stage least squares model to address endogeneity, our analysis shows that DFS access induces a structural change from self-employment to formal employment, with men experiencing a more pronounced transition, particularly from agricultural self-employment to non-agricultural self and wage employment. For women, the shift is marked by a reduction in unpaid self-employment and an increase in wage employment. At the intensive margin, the non-switchers, irrespective of gender and the type of employment, see higher earnings and time spent in employment. Additionally, DFS access reduces time allocated to domestic responsibilities alongwith greater use of banking services, the internet, and digital payment platforms.

JEL classifications: G21, J16, J22, O33, O16
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1 Introduction

As of 2023, the global digital payments market was valued at approximately $8.49 trillion, with projections indicating it will surpass $15 trillion by 2027, driven by the rapid adoption of mobile payments, digital banking, and Fintech innovations, particularly in developing economies (Statista, 2023; Insights, 2023). Digital Financial Services (DFS) have transformed the way economic transactions are conducted, particularly in developing economies. By lowering transaction costs, expanding financial inclusion, and enhancing access to credit and consumption, DFS have emerged as powerful drivers of economic growth and poverty alleviation (Jack and Suri, 2014; Suri and Jack, 2016; Demirguc-Kunt et al., 2018; Higgins, 2019; De Mel et al., 2022; D'Andrea and Limodio, 2024; Cong, Giesecke, and Kuhnen, 2024; Shapiro and Mandelman, 2021; Agarwal et al., 2024). While these macroeconomic effects are well-established, the microeconomic impact of DFS on labor market reallocation, especially through a gendered lens, remains underexplored. This paper provides new insights by examining how DFS facilitate labor transitions from informal to formal employment, and time spent in labor and non-labor activities, with a particular focus on gender disparities and the impact of DFS on both self-employment and wage employment.

The central question of this paper is whether and how the diffusion of DFS drives a structural transformation in employment patterns, shifting labor from informal, subsistence-based activities toward more formal and productive roles. Additionally, the paper explores how this transformation may vary by gender, investigating whether the mechanisms through which DFS influence labor market outcomes differ for men and women. This is particularly relevant in developing countries such as India, where much of the labor force remains entrenched in informal agricultural self-employment (Kundu, 2020; Abraham, 2017), and where gender disparities in labor market participation are especially stark (Jayachandran, 2015; Bertrand et al., 2021; Field et al., 2021). By examining both the extensive margin (likelihood of employment) and the intensive margin (time spent on employment and wages) across different types of employment, we contribute to a robust understanding of the labor market dynamics across genders.

The paper hypothesizes that the expansion of DFS facilitates this transformation, yet through different mechanisms for men and women. For men, we hypothesize that increasing access to DFS leads to a decline in agricultural self-employment. This transition can be understood through the lens of structural change theories (Lewis et al., 1954; Boppart and Krusell, 2020), which posit that as economies modernize, labor tends to shift from sub-

sistence agriculture to more productive sectors, such as non-agricultural self-employment and wage labor. DFS, by reducing transaction costs and expanding access to credit (Suri and Jack, 2016), are likely to accelerate this process by facilitating access to formal credit markets and increasing the productivity of labor in non-agricultural sectors. While Shapiro and Mandelman (2021) argue that firms adopting digital technologies often result in workers transitioning out of self-employment into wage labor, we argue that this overlooks an important dynamic: rather than simply exiting self-employment, men could be reallocating into non-agricultural self-employment. This suggests that DFS are not merely driving a move into formal wage labor, but also facilitating a reallocation within self-employment from low-productivity agricultural activities to higher-productivity, non-agricultural sectors, highlighting that this transition is more about productivity rather than a direct leap from one sector to another.

For women, DFS offer a distinct set of opportunities. Historically, women have been disproportionately excluded from formal labor markets due to structural barriers, including unpaid domestic responsibilities and limited access to financial resources (Duflo, 2012; Barth, Kerr, and Olivetti, 2021; Exley and Kessler, 2022). By providing women with access to banking services, mobile payments, and digital credit, DFS can help reduce these barriers and unlock new pathways into formal employment. From a theoretical perspective, increased access to financial services enhances women's bargaining power both within the household and in the labor market, as outlined by theories of gender empowerment and economic autonomy (Duflo, 2012; Bertrand et al., 2021). This shift is expected to facilitate greater participation in the formal economy and help women move away from unpaid and unrecognized labor, thereby altering traditional gender roles. However, we expect that the magnitude of this shift may be smaller for women than for men, given the deeper structural challenges women face in entering formal labor markets (Jayachandran, 2015; Bertrand et al., 2021).

To test these hypotheses, we use nationally representative data from the Periodic Labor Force Survey (PLFS), Indian Time Use Survey (ITUS), and the National Family Health Survey (NFHS). These datasets provide a rich basis for understanding labor market participation, digital financial inclusion, and time-use patterns disaggregated by gender, allowing us to explore both the demand- and supply-side effects of DFS on labor markets. Our empirical strategy employs a two-stage least squares (2SLS) approach to account for potential endogeneity in the adoption of DFS. Following the methodologies outlined by Chodorow-Reich et al. (2020), Crouzet, Gupta, and Mezzanotti (2023) and Das et al. (2023), we instrument DFS access using district-level exposure to 'bank chest' infrastructure. This

approach allows us to address potential endogeneity concerns by isolating the exogenous variation in DFS access that is driven by historical banking infrastructure rather than by current economic conditions. This strategy mitigates concerns about unobserved confounders that may simultaneously influence both employment outcomes and DFS, thereby strengthening the causal interpretation of our results. We employ alternative estimation models and variations of the DFS variable to ensure robustness of the 2SLS estimates.

Our findings at the extensive margins offer critical insights into how DFS influence both the structure of employment and the allocation of labor across sectors. For men, while the overall reduction in self-employment is substantial, the increase in non-agricultural self-employment underscores a more productive transformation. Men are not merely exiting self-employment but reallocating toward more productive roles, reflecting a strategic shift from subsistence farming to non-agricultural sectors where DFS-driven financial access can be leveraged for growth. For women, the results show a marked decline in unpaid self-employment and agricultural self-employment and a corresponding increase in formal wage employment, further supporting the hypothesis that DFS facilitate a reallocation of labor from informal, unpaid roles to more secure, remunerative work. Our findings are consistent with Suri and Jack (2016) who in Kenya find that "the impact of mobile money is pronounced for female-headed households, driven by changes in financial behavior—in particular, increased financial resilience and saving—and labor market outcomes, such as occupational choice, especially for women, who moved out of agriculture and into business". While the absolute changes for women in our analysis appear smaller, their relative gains in employment and economic autonomy, compared to their initial baseline, are pronounced and suggest a deeper transformation in how labor is allocated across gender lines.

At the intensive margin, conditional on positive time spent in the employment activity, we find that DFS significantly increased the time men allocate to both self-employment and formal wage employment. For women, the impact of DFS is more pronounced in formal wage employment, but we also observe a meaningful increase in time spent on self-employment. This dual effect indicates that while DFS facilitate deeper integration into formal labor markets, they simultaneously lead to greater involvement in entrepreneurial activities for women. Importantly, the increase in time spent on employment for both men and women appears to be driven by a reduction in time allocated to unpaid care work and self-care activities. Moreover, our analysis reveals significant wage gains across both self-employed and regularly employed individuals. Crucially, the absence of statistically significant differences in wage increases between genders suggests that DFS promote wage

growth in an equitable manner, contributing to narrowing the relative gender wage gaps. These findings underscore the broader potential of DFS to drive not only economic expansion but also to foster more inclusive and equitable labor markets.

Insights from the NFHS further highlight the socio-economic transformations brought about by DFS, showing how these technologies extend beyond macroeconomic impacts to affect individual-level outcomes, particularly in terms of financial inclusion and autonomy. The widespread adoption of DFS has significantly increased the ownership of bank accounts, mobile phones, and use of internet—enablers of digital economy across genders. For women in particular, these technologies have fostered a marked increase in financial autonomy, granting them greater control over financial resources. This empowerment of individuals—especially women—represents a broader reallocation of economic power, wherein DFS not only reshape employment dynamics but also reduce gender disparities in financial access and decision-making authority.

Crucially, the demand-side effects of DFS must be considered alongside the supply-side dynamics. While the expansion of DFS at the district level facilitates greater formal employment opportunities, the direct engagement of individuals with DFS tools—through the increasing use of mobile payments and internet banking—drives additional transformations in labor markets. This demand-side adoption of DFS enhances men's and women's ability to participate in the formal economy, expanding their economic agency. By examining both supply- and demand-side impacts of DFS, this paper provides new insights into how digital tools are reshaping labor markets, fostering formal employment growth, and transforming economic agency.

Our heterogeneity analysis reveals that DFS impact labor market outcomes differently across demographic groups, and production of goods and services, uncovering distinct economic behavior patterns. Disaggregating by gender across age, education, marital status, and social groups, we observe notable differences in time allocation in employment. Younger and more educated individuals, adaptable to digital integration, are more likely to increase their time spent on employment activities. Marital status also plays a role, with unmarried individuals responding more strongly to DFS, while social categories further shape outcomes, with benefits accruing to the privileged, reflecting the role of socio-economic factors in mediating the benefits of DFS. These findings echo Aziz and Naima (2021), who identified similar dynamics in Bangladesh, where skills and demographics mediate the impact of Information Communication and Technology (ICT) infrastructure and DFS availability. Additionally, we find that both employed men and women shift their time spent from pro-

duction of goods to services. Our heterogeneity analysis highlights the pathways through which DFS reshape labor markets and underscores the importance of targeted interventions for inclusive growth.

To ensure robustness, we conducted three analyses disaggregated by gender to verify the direction and consistency of the estimated effects. First, IV estimates were compared with OLS results, affirming the direction of observed effects of DFS on employment and wage outcomes. Second, alternative specifications of DFS exposure—using both transaction counts and growth of DFS from 2018 to 2019—confirmed the stability of our findings. Third, extending the analysis to the post-COVID period using NFHS, 2021, data showed that while some results became statistically insignificant as expected, the overall trends remained consistent. These analyses demonstrate that the impact of DFS on labor market outcomes is robust across different methodological approaches and time periods.

2 Literature Review

The rapid expansion of DFS has become central to economic research due to its potential to enhance financial inclusion, reduce transaction costs, and drive economic development, particularly in developing countries. Seminal works by Suri and Jack (2016), Mbiti and Weil (2015), and Jack and Suri (2014) highlight how mobile money platforms like M-Pesa in Kenya have facilitated economic growth by providing unbanked populations access to financial services, reducing credit constraints, and enabling consumption smoothing. These studies underscore the macroeconomic benefits of DFS, including poverty alleviation and economic empowerment. Similarly, Demirguc-Kunt et al. (2018) and Shapiro and Mandelman (2021) explore how DFS can address poverty, hunger, and gender inequality, while also driving sectoral labor market shifts at a cross-country level. While these works provide important macro-level insights, the microeconomic mechanisms, particularly the gender-specific effects and intra-household labor dynamics, remain largely underexplored.

Our study fills this gap by providing a micro-level analysis of the gender-differentiated impacts of DFS on labor supply, focusing on both the extensive and intensive margins of employment. We examine how DFS reshape labor allocation within households, leading to structural shifts between formal and informal employment, especially in gender-unequal economies. This focus on labor reallocation provides new insights into how DFS influence labor market transitions beyond the macro-level impacts discussed in previous studies. For instance, while Agarwal et al. (2024) analyze India's 2016 demonetization and its effect on

accelerating digital payments with a focus on liquidity constraints and consumer spending, we extend this by exploring how DFS facilitate formal employment entry, particularly for women, contributing not only to consumption smoothing but also to employment growth and higher-paying job opportunities. Dubey and Purnanandam (2023) analyze district-level DFS data to explore its role in fostering economic growth and entrepreneurship. In contrast, we employ district-level data from PhonePe Pulse to examine how DFS influence labor market transitions, specifically focusing on shifts in the nature of employment, unpaid work, and the allocation of time between labor and non-labor activities. Our analysis offers a more granular examination of productivity gains, particularly within self-employment, providing a nuanced understanding of how DFS reshape labor dynamics beyond their impact on entrepreneurship.

In addition to the macroeconomic insights, randomized controlled trials (RCTs) have shed light on the demand-side impacts of DFS on financial inclusion. Field et al. (2021) demonstrate that access to individual bank accounts enhances women's financial autonomy and alters their labor supply decisions. Similarly, Riley (2018) provide experimental evidence from Tanzania showing how mobile money improves risk-sharing and helps households smooth consumption in response to shocks, particularly benefiting women. Further, De Mel et al. (2022) and Cole, Joshi, and Schoar (2024) explore how mobile-linked accounts and mobile-based business advice foster improvements in savings behavior and entrepreneurial outcomes. While these RCTs underscore the demand-side benefits of DFS, they leave largely unexplored the supply-side mechanisms, such as labor market transitions and time-use adjustments in response to aggregate changes in digital payments at the regional level. Our study fills this gap by employing an instrumental variable approach to deliver a nationally representative analysis of how DFS drive labor market transitions, with a particular focus on gender-specific shifts from informal to formal employment and the reallocation of time between labor and non-labor activities.

Beyond household-level effects, prior research has examined the broader impacts of DFS on various economic outcomes. Studies have addressed savings and insurance (De Mel et al., 2022), liquidity and consumption smoothing (Agarwal et al., 2024), risk-sharing (Carli and Uras, 2024), migration responses and resilience to economic shocks (Chen and Zhao, 2021; Riley, 2018; Suri, Bharadwaj, and Jack, 2021; Londoño-Vélez and Querubin, 2022; Batista and Vicente, 2023), agricultural growth (Aker, 2010; Aggarwal, Brailovskaya, and Robinson, 2023), remittances (Pazarbasioglu et al., 2020; Moorena et al., 2020), technology adoption (Crouzet, Gupta, and Mezzanotti, 2023), entrepreneurship and economic development

(Dubey and Purnanandam, 2023; Beck et al., 2018; Cole, Joshi, and Schoar, 2024), and tax returns (Das et al., 2023). However, these studies largely overlook the micro-level, causal implications for labor markets, particularly in gender-unequal settings. Our study contributes by examining how DFS adoption reallocates labor between formal and informal sectors, reshaping employment for both men and women.

We further build on Shapiro and Mandelman (2021), who find that firm-level digital adoption reduces self-employment by facilitating transitions into salaried jobs. Our study also finds that DFS reduce overall self-employment, but we uncover a key distinction: this reduction reflects a shift within self-employment from low-productivity agricultural work to higher-productivity non-agricultural activities. By highlighting these internal transitions, we offer a more disaggregated understanding of how DFS promote productivity-enhancing labor reallocations beyond simple labor market shifts.

In conclusion, while previous research has primarily focused on the aggregate effects of DFS on consumption smoothing, gender autonomy, and macroeconomic outcomes, our study advances the literature by offering a detailed, micro-level analysis of how DFS reshape labor markets. By addressing both the extensive and intensive margins of employment, with a focus on intra-household labor dynamics, our research fills critical gaps in the literature and provides new insights into how DFS drive inclusive economic growth and promote gender equality in labor markets.

3 Data

We use five main datasets for our analysis of the impact of digital finance on gendered time use patterns: UPI usage data from Phonepe, Indian Time Use Survey (ITUS), National Family Health Survey (NFHS), Periodic Labor Force Survey (PLFS) and RBI data on Currency Chests. The details of the datasets are discussed below.

3.1 UPI usage data from Phonepe

We extract the district-level UPI usage data from Phonepe, which is one of India's largest UPI platforms founded in 2015. In September 2021, Phonepe launched 'Phonepe Pulse', which is an online repository of the digital transaction data from Phonepe users, available for each quarter from the year 2018. We used the data API available on Pulse webpage and scraped the data. Our district-level treatment variable is the average of the total amount of digital transactions over the years of 2018 and 2019. To add an additional layer of

robustness, we use the total count of digital transactions averaged over the same period and the growth of digital transactions between 2018 and 2019 as an alternative treatment variable. The summary statistics of UPI usage are presented in Table A1. Additionally, in panel (a) of Figure 1, we show a district-level map of the intensity of UPI usage in 2019 (measured in total value of transactions) and in panel (b), we show another map of growth in UPI usage in between 2018 and 2019, measured in terms of the difference in log values of the amount transacted in 2018 and 2019.

3.2 Indian Time Use Survey (ITUS)

Time-use surveys offer a framework for gauging how much time people spend on various activities, whether they are paid, unpaid, or other. In India, the first time-use survey was a pilot conducted in six states of India (Gujrat, Meghalaya, Tamil Nadu, Haryana, Orissa and Madhya Pradesh) during 1998-1999. Thereafter, during January-December 2019, National Statistical Office (NSO) conducted the first pan-India Time Use Survey.

ITUS covered 1,38,799 households, among which 82,897 were from rural areas and the remaining 55,902 were from urban areas. Time use patterns of each household member aged 6 and above were collected, which aggregated to a total of 4,47,250 individuals. The survey, conducted through personal interviews, recorded information on time use for a period of 24 hours, beginning the day before the interview at 4:00 A.M. and ending at 4:00 A.M. on the day of the interview.

The gender-disaggregated data on time use patterns in ITUS allow us to study time spent on employment activities by men and women separately. For a more detailed understanding, we look at time spent on regular employment, self-employment and casual employment, alongside the total time spent on all employment activities. We also analyze time spent on unpaid activities, learning and socializing activities and self-care, to better understand the underlying mechanisms. Our sample is restricted to individuals above age 14. In Table 1, we present a detailed summary statistics of the intensive margin of time use variables, for both males and females, which we use for our main results. In Table A1, we present another set of time use statistics, which we use for additional results and robustness checks.

3.3 National Family Health Survey (NFHS)

NFHS is a large-scale household survey conducted by the Ministry of Health and Family Welfare that captures a wide range of topics covering women's health, autonomy, domestic

violence, fertility, etc. For our analysis, we focus on the fifth round of NFHS, which was conducted in two rounds in between 2019 and 2021. We draw the following individual-level information from NFHS for men and women separately: (a) Do they own a bank account? (b) Do they own a mobile phone? (c) Do they use their mobile phones for financial transactions? (d) Do they use the internet? and (e) Do they have access to money that they can use as they wish? The last piece of information is only there for women, but not for men. For men, the data comes from the men's recode and for women, the data comes from the individual recode.

The data for women is drawn from the eligible women dataset of NFHS, where the sample is restricted to women in between the age group of 15-49. Men's data is drawn from men's dataset, where no age restriction is put. To make our results consistent and comparable with women's data, we restrict our sample to 15-49 age group for men's data as well.

3.4 Periodic Labor Force Survey (PLFS)

PLFS is a rich source of data on the employment and unemployment situation in India. The survey is being conducted annually by the National Statistical Office (NSO) since 2017. For our analysis, we use the 2019-20 wave of PLFS, which was conducted between July 2019 and June 2020. The pan-India survey covered 6,913 villages and 5,656 urban blocks, including a total of 4,18,297 individuals (2,40,231 in rural areas and 1,78,066 in urban areas). We use the gender-disaggregated data on the extensive margin of employment activities from PLFS 2019-20, including self-employment, unpaid self-employment, regular employment and casual employment. We also use the information on individual wages in regular employment and earnings in self-employment. It is worth noting that the data for overall wages/earnings and wages for casual employment are not available in PLFS. To make our analysis consistent with ITUS, we restrict our sample to individuals over age 14 in PLFS as well. In Table 1, we present the summary statistics of the variables we use from PLFS.

3.5 RBI data on Currency Chests

A few scheduled banks have been given permission by the Reserve Bank to set up currency chests in order to make it easier to distribute rupee coins and banknotes. These are repositories where the Reserve Bank stocks rupee coins and banknotes for distribution

to bank branches within their service region.[1] We obtain the district-level data on the number of currency chests curated by Crouzet, Gupta, and Mezzanotti (2023), which was originally sourced from RBI. There are 512 districts in this dataset, excluding districts from northeastern states and union territories. For the purpose of our analysis, we merged this district-level data with ITUS and NFHS separately.

4 Instrumental Variable and Methodology

To analyze the impact of digital financial transactions on gendered time-use patterns, addressing potential endogeneity is crucial. Endogeneity may arise from self-selection, where individuals, especially women, in economically prosperous regions adopt online payment systems and use their time more efficiently due to existing economic advantages. Additionally, reverse causality may occur if individuals engaged in employment activities seek out digital transactions to save time. These scenarios can bias OLS estimates, compromising the validity (bias and efficiency) of the estimates.

To mitigate these concerns, we employ an IV approach. We instrument district-level digital transactions using the currency chest exposure index, Chest_d, for each district. This choice is inspired by Crouzet, Gupta, and Mezzanotti (2023), followed by Aggarwal, Kulkarni, and Ritadhi (2023) and Das et al. (2023), who leveraged historical variations in banking infrastructure, specifically chest banks, as an exogenous source of variation. The chest exposure index, Chest_d, measures the proportion of total deposits in a district held by banks operating currency chests. This index reflects the significance of these banks in each district, derived from detailed deposit and branch data. The relationship is given by:

$$\text{Chest}_d = \frac{\sum_{b \in C_d} \omega_j D_{jbd}}{\sum_{b \in B_d} \omega_j D_{jbd}},$$

where C_d is the set of banks operating currency chests in district d, B_d is the set of all banks in the district, ω_j is a weighting factor for each bank, and D_{jbd} represents the deposits by bank b of type j in district d.[2] Higher Chest_d scores indicate easier access to cash, reducing

[1] As of March 31, 2024, 2,794 money chests were in existence.

[2] To weighting factor, ω_j is determined based on factors such as the size of the bank, the volume of cash transactions it handles, and its operational scope in managing currency chests. For instance, banks with larger networks and higher volumes of cash handling may be assigned a higher ω_j, reflecting their greater impact on cash availability in the district (Crouzet, Gupta, and Mezzanotti, 2023). This method allows the measure Chest_d to account for not just the presence of banks with currency chests, but also their operational significance in the local cash economy.

reliance on digital transactions.

Using Chest_d as an IV addresses endogeneity by capturing variations in cash availability across districts. This natural experiment setting allows us to isolate the effect of cash access on digital financial transaction adoption. The strong negative correlation between Chest_d and cash availability establishes its relevance as an IV. The exogeneity is ensured by the historical stability of currency chest locations, determined by logistical considerations independent of recent digital transaction trends.

The validity of an IV relies on satisfying two primary conditions: relevance and exclusion restriction. The relevance condition is met as Chest_d significantly influences the availability and adoption of digital payment systems. Historical data indicates that the distribution of chest banks significantly affects the local financial infrastructure's capability to support digital transactions (Crouzet, Gupta, and Mezzanotti, 2023). Chest banks play a crucial role in ensuring liquidity and cash management, thereby facilitating the adoption of digital payments. Empirical evidence supports this claim, showing that a higher number of chest banks in a district implies greater access to cash and a lower likelihood of cash shortages, thus enhancing the adoption of digital payments (Aggarwal, Kulkarni, and Ritadhi, 2023). Therefore, Chest_d is a strong predictor of digital financial transaction volumes. To substantiate this assertion within the context of our dataset, we present a two-way scatterplot with a linear fit in Figure A1. The inverse relationship between the chest exposure index and our principal treatment variable (log of the amount transacted) is evident, reflecting a negative correlation coefficient of -0.33.

The placement of chest banks, determined by the Reserve Bank of India (RBI) based on historical and logistical factors, is unrelated to current time-use patterns or economic behaviors at the household level (Crouzet, Gupta, and Mezzanotti, 2023). Therefore, it is reasonable to assume that chest banks influence time-use patterns exclusively through their impact on digital financial transactions.

Complementarities in the adoption of digital financial services plays a key role in the validity of our instrument. Complementarities arise when the benefits of adopting digital financial services increase with the number of users. These dynamics further justify using district-level exposure to banking infrastructure as an IV, capturing spatially exogenous variations in the availability and promotion of digital financial services. To estimate the causal impact of digital financial transactions on gendered time-use patterns, we use a Two-Stage Least Squares (2SLS) model, which involves the following steps:

$$D_{ds} = \delta C_{ds} + X'_{ids} + Z'_{ds}\gamma + \alpha_s + \epsilon_{ids}, \tag{1}$$

where D_{ds} is the amount of digital transactions (measured in log) in district d and state s, averaged over 2018 and 2019. C_{ds} is the chest bank exposure in district d and state s. X_{ids} is a vector of individual-level controls, including age, age squared, religion, gender of household head, education of household head, household size, and the day of the week when the interview was conducted. Z_{ds} is a vector of district-level controls, including the number of ATMs and commercial banks. α_s represents state fixed effects, and ϵ_{ids} is the random error term.

The first stage regression estimates the relationship between the number of chest banks and the amount of digital transactions, controlling for individual and district-level characteristics. The second stage regression is:

$$Y_{ids} = \beta D_{ds} + X'_{ids} + Z'_{ds}\gamma + \alpha_s + \epsilon_{ids}, \tag{2}$$

where Y_{ids} is the outcome variable of interest for individual i residing in district d. The other variables are as defined in the first stage. In this stage, the main coefficient of interest (β) captures the causal impact of digital financial transactions on time-use patterns. To ensure the robustness of our results, we conduct alternative specifications test by using the growth and count of digital transactions as the treatment variable. We analyze the effects separately for different demographic groups to understand the heterogeneity in the impact of digital financial transactions on time-use patterns.

5 Results

In this section, we present gender-disaggregated results on the structural transformation patterns, arising from an expansion of DFS. We use a 2SLS estimation strategy detailed in section 4, where digital payments are instrumented with district-level exposure to the currency chests. We start with estimating the gender-disaggregated impact of digital payments on the extensive margin of employment,[3] presented in Table 2. Column (1) reports the estimates for overall employment, and in columns (2), (3) and (4), we further decompose overall employment into self-employment, regular employment and casual wage employment.

[3]For our extensive margin results, the comparison group of an employed individual is unemployed and out of labor force individuals.

5.1 Extensive Margin: DFS and Employment

For both men and women, we find a null effect on the overall employment, but after the decomposition of employment types, we observe a noticeable shift in the types of employment. For men, with 1% increase in the district-level average amount transacted digitally, the likelihood of self-employment and casual employment reduces by 3.7 and 1.1 percentage points (pp), respectively. The total reduction is offset by an equal increase in the likelihood of regular wage employment by 4.8 pp. Therefore, men are found to be transitioning from informal employment activities to more formal, wage-based roles. In Panel (B), we carry out the same analysis for women. We find a positive and significant impact of 1.6 pp in regular wage employment and an almost equal but negative impact of 1.0 pp on casual wage employment. However, we do not find any significant impact on the self-employment of women.

To examine the underlying mechanism of this shift in employment patterns from self-employment to formal employment, we decompose employment into agricultural and non-agricultural sectors. More specifically, we focus on agricultural and non-agricultural self-employment, along with unpaid self-employment. The estimated coefficients using 2SLS are presented in Table 3. For men, we observe a 7.7 pp decline in overall agricultural employment and a similar increase in overall non-agricultural employment. Furthermore, within self-employment, we show a 6.4 pp decline in agricultural self-employment and a 2.7 pp increase in non-agricultural self-employment. As the magnitude of the decline is much higher than the magnitude of the increase, these results are consistent with our observed decline in overall self-employment in Table 2. This is a case of structural change, where a shift from subsistence agriculture to a more productive sector is observed. This hypothesis is further supported by the observed decline in unpaid self-employment by 0.9 pp, in column 5 of Table 3. Similarly, for women, we see a reduction in overall agricultural employment and an increase in overall non-agricultural employment. While agricultural self-employment declines by 0.7 pp, non-agricultural self-employment does not seem to have any statistically significant impact, although the magnitude is positive and nearly equal to agricultural self-employment. As a result, we observe a statistically insignificant impact on women's self-employment in Table 2.

5.2 Intensive Margin: DFS and Time-use in Paid and Unpaid Activities

We complement the insights from the extensive margin with an additional analysis of the intensive margin of employment using ITUS data. The results are furnished in Table 4.

At the intensive margin (conditional on positive time spent on the activity on a typical day), we focus only on employed individuals and investigate whether they devote more time to paid employment activities in districts with higher levels of digital payments. The analysis is conducted separately for overall/any employment, self-employment, regular wage employment and casual wage employment and the estimates are reported in columns (1), (2), (3) and (4), respectively. In Panel A, we find that men who are employed, spend an additional 7.32 minutes on paid activities with 1% increase in the average amount of digital payments in the district. As compared to the sample mean, it shows a gain of nearly 1.78% in time spent on paid activities. The impact on self-employed men is found to be 8.63 minutes, which indicates an increase of nearly 2.18% compared to the respective sample mean.[4] A positive gain of 4.63 minutes is observed for men in regular-wage employment, implying a gain of 1.05%.

For women, the intensive margin results are mostly similar to men, except that we do not observe any statistically significant impact on the overall employment minutes. While the impact for employed women is found to be absent in Column (1), it is positive for those who are self-employed or regular-wage employed. To be precise, self-employed females spent 10.6 minutes more on paid activities with a 1% increase in digital payment, which is equivalent to 3.4% of the sample mean. Similarly, for women in regular-wage employment, the gain in minutes is 7.73 which is significant at 5% level. It indicates a gain of 2.1% compared to the sample mean in this category. The analysis of minutes spent complements what we found in Table 2. While there is a marginal decline in overall employment for men in Table 2, there is a positive gain on the intensive margin i.e. the minutes spent. The gender-disaggregated analysis on minutes spent also shows that the measured impact is relatively higher for females.

Next, we investigate if the positive gains observed at the intensive margin for paid activities are led by a reduction in time allocated to unpaid activities. Specifically, with an increase in digital payments within a district, individuals may reallocate their time from unpaid activities to paid activities. This shift could be attributable to (i) the increased convenience of digital transactions, which reduces the need for in-person banking or other financial interactions and (ii) the greater availability of gainful employment (for example, regular employment) increases the opportunity cost of unpaid work, especially for women, allowing them to redistribute their time from unpaid to paid work. These factors could act as

[4] At the extensive margin, we found a decrease in self-employment, which implies that men are moving out of self-employment. But at the intensive margin, we focus on those who remain self-employed, and for them, the minutes spent on self-employment activities increase.

underlying mechanism that explains the positive gains in time spent on employment.

We divide all unpaid activities into 3 categories: time spent on unpaid domestic and caregiving activities; learning, social and cultural activities; and self-care. The estimates for men and women are reported in Table 5, where we restrict our sample to employed individuals. For employed men (Panel A), time spent on unpaid domestic and employment activities reduces by 3.88 minutes, and time spent on self-care reduces by 5.76 minutes. Similarly, for women, time spent on unpaid care and home production, and self-care reduces by 9.09 and 5.25 minutes respectively. However, unlike men, the time spent on learning, social and cultural activities by women increases significantly by 9.35 minutes. This could be because of higher access to mobile phones, as will be discussed in section 5.3. This implicates a potential shift of women from unpaid care activities to self-development activities, which could help them gain desirable skills for employment opportunities in the long run.

Following our analysis of employment activities, we investigate the impact of DFS on earnings. The data on earnings for self-employment and regular wage employment activities are sourced from PLFS. It is important to note here that PLFS does not provide any data on earnings for overall employment and casual employment. The gender-disaggregated results for earnings are presented in Table 6. We find that the absolute increases in earnings (measured in INR) are higher for men (INR 1108.24 and 1235.9 for self and regular employment respectively) compared to women (INR 629.06 and 1140.7). However, the percentage increases in both self and regular employment are higher for women (12.55% and 16.07%) compared to men (10.21% and 13.15%). This indicates an equitable growth in the earnings for men and women.

5.3 Demand Side Effects of Digital Finance

So far, we have studied the impacts on the supply side in terms of shifts in employment patterns in the labor market. However, for a comprehensive understanding of the impacts of digitization, we need to bring in the demand side as well. We use data from NFHS to analyse individual-level interaction with DFS tools. Specifically, we focus on four enablers of digital transactions for men and women- ownership of bank accounts, ownership of mobile phones, use of internet and use of mobile for financial transactions. Additionally, for women, we assess financial autonomy—defined as access to money that they can use independently—to gauge their control over financial resources. The findings, detailed in Table 7, reveal a general increase in bank account ownership, mobile phone usage for financial transactions, and internet usage for both men and women. Notably, the likelihood of owning a mobile

phone increases significantly only for women, by 6.7 pp. Moreover, women experience a 4.6 pp gain in financial autonomy, reflecting a greater likelihood of having access to money for personal use. Moreover, an increase of 2.2 pp in the likelihood of owning bank account for women, along with the insignificant difference between men and women in owning bank account, indicates an increase in the likelihood of access to credit which is consistent with the findings of Agarwal et al. (2024).

In Table 7, we use data from wave 1 of NFHS-5, which was conducted before Covid-19 outbreak in 2020. In Table A2, we run the same model using data from wave 2, conducted after COVID-19. As Covid made social distancing mandatory, it had a large confounding impact on DFS usage, which weakens our instrumental variable to a great extent. For example, the F-stat from the first stage was 14.92 for bank account ownership of men in wave 1, which reduced to 1.98 in wave 2. Weak instrumental variable explains the insignificant post-covid estimates.

5.4 Heterogeneity Analysis

We carry out a series of heterogeneity analyses to understand how the impacts of DFS on extensive and intensive margins of employment, and sectoral analysis, differ for different socioeconomic groups.

The heterogeneity analysis of the impact of DFS on the intensive margin of time use in employment in Figure 3 reveals notable gender and demographic differences. For men, the impact is generally smaller across all groups, with the most significant effects observed among those with higher education levels and older age. For women, those with higher education, older age, and from higher social groups (General and OBC) experience the largest increases in employment time. In contrast, disadvantaged groups such as Scheduled Castes and Scheduled Tribes, and those with lower education levels, see more limited or insignificant effects for both men and women. Additionally, married women benefit more from DFS than their unmarried counterparts, suggesting that DFS offers greater flexibility and support for balancing household responsibilities with paid work. Overall, these findings highlight the uneven benefits of DFS, particularly favoring educated and higher-status individuals, while emphasizing the need for inclusive policies to bridge the gap for lower-educated and marginalized populations.

The heterogeneity analysis of the impact of DFS on time spent in the production of *goods* vs *services*, as shown in Table A3, reveals distinct gendered patterns across employment cate-

gories. For men, DFS significantly reduce the time allocated to goods production, especially among the self-employed, while increasing time spent on service production, highlighting a shift in labor allocation from goods to services. Regular and casual wage-employed males show less significant effects, suggesting that the impact of digital transactions is more pronounced in self-employment contexts, also found in our analysis at the extensive margin. In contrast, women experience a significant increase in time spent on service production, particularly among regular wage workers, while the effects on goods production are either insignificant or modestly negative. These results suggest that digital financial services facilitate a reallocation of labor towards service-oriented activities, particularly benefiting women and self-employed men, and potentially indicating a broader structural transformation in time use patterns. To further substantiate the significant effects on self-employment for men, in Table A4, we look at the impacts on unpaid activities by employment categories. The reduction in time spent on unpaid activities is coming mainly from self-employed men. In contrast, women from regular wage employment experience a reduction in unpaid activities (also found in the extensive margins analysis in Table 3), and self-employed women see an increase in learning, social and cultural activities.

5.5 Robustness Checks

We carry out an array of robustness checks to maximize the confidence in our estimates. First, we use OLS to re-estimate our main results. In Table A5, we present the OLS estimates of the extensive margin of types of employment dummies from PLFS. Similarly, in Table A6, we show the OLS estimates of intensive margin (time use) for paid employment activities, separately for different employment types. Our results using OLS are consistent with the 2SLS estimates.

Secondly, we use the average log count of digital transactions between 2018 and 2019 as an alternative treatment variable, instead of average log amount of digital transactions. The results are produced in Table A11 for extensive margin of employment and in Table A7 for intensive margin of employment, again for four types of employment categories: all employment, regular wage employment, self-employment and casual employment. We find that the results are consistent with our main results.

Thirdly, we use the growth in the amount of digital transactions between 2018 and 2019 as an alternative explanatory variable. Growth is measured as the log difference between amounts transacted in 2018 and 2019. We present the extensive margin results in Table A12 and intensive margin results in Table A8, which are found to be consistent with our

original set of results. In Table A10, we show that the results from NFHS are consistent as well.

Finally, we construct extensive margin indicators for different types of employment using ITUS, and run the 2SLS model to check its consistency with extensive margin results from PLFS. The results, presented in Table A9, show similar switch from self-employment to regular employment for men and switch from casual to regular employment for women[5].

6 Conclusion

The paper examines the impact of DFS on labor market dynamics, with particular attention to gendered outcomes. Our findings demonstrate that DFS foster significant shifts in employment structure, particularly transitioning labor from agricultural to non-agricultural sectors. For men, this transition is marked by a notable decline in agricultural self-employment, accompanied by a rise in non-agricultural employment and regular wage employment, reflecting a broader movement toward more diversified economic activities. Women, meanwhile, experience a substantial reduction in unpaid self-employment, with a corresponding increase in regular wage employment, signaling improved access to formal labor markets. This transition for women is especially critical in breaking traditional gender roles, as they move out of unpaid, informal sectors into more secure, income-generating work.

On the intensive margin, the introduction of DFS significantly boosts time spent in labor across both self-employment and regular wage employment, leading to notable wage gains for both men and women. This wage growth is critical for narrowing the gender wage gap, as women experience comparable gains, contributing to greater gender equality in labor market participation. Furthermore, the redistribution of time from unpaid domestic and caregiving activities to productive employment, particularly for women, signals a reallocation of household labor that is essential for promoting gender equity.

Additionally, DFS enhance financial autonomy for both men and women by increasing access to banking services and enabling mobile based financial transactions. For men, this improved financial inclusion opens up opportunities to diversify income sources, particularly in non-agricultural sectors, fostering economic growth. For women, greater access

[5]Some of our robustness checks, we observe a reduction in overall employment for men, which is different from the null effect in our main results. It could potentially arise from the fact that regular wage pays more than self-employment and hence regular employment grows at a lesser rate, which could make the overall employment negative.

to banks, mobile phones, internet and use of DFS empower them to engage more fully in wage-based employment and formal financial systems, thereby expanding their economic agency. The increased use of formal financial instruments by both genders supports greater financial independence within households and encourages more equitable economic participation, leading to improved household financial security and broader engagement in formal economic activities.

Overall, this paper demonstrates that DFS act as a catalyst for structural change in the labor market, reshaping traditional gender roles by reducing disparities in both labor market and financial inclusion. The transformative potential of DFS lies not only in fostering labor market participation but also in driving social change by promoting gender equity and economic empowerment for women. The long-term implications of these findings suggest that the widespread adoption of DFS could be pivotal in achieving gender equitable and sustainable labor market outcomes.

References

Abraham, Rosa. 2017. "Informality in the Indian labour market: An analysis of forms and determinants." The Indian Journal of Labour Economics 60:191–215.

Agarwal, Sumit, Pulak Ghosh, Jing Li, and Tianyue Ruan. 2024. "Digital Payments and Consumption: Evidence from the 2016 Demonetization in India." The Review of Financial Studies 37 (8):2550–2585. URL https://doi.org/10.1093/rfs/hhae005.

Aggarwal, Bhavya, Nirupama Kulkarni, and SK Ritadhi. 2023. "Cash is king: The role of financial infrastructure in digital adoption." The Review of Corporate Finance Studies 12 (4):867–905.

Aggarwal, Shilpa, Valentina Brailovskaya, and Jonathan Robinson. 2023. "Saving for multiple financial needs: evidence from lockboxes and mobile money in Malawi." Review of Economics and Statistics 105 (4):833–851.

Aker, Jenny C. 2010. "Information from markets near and far: Mobile phones and agricultural markets in Niger." American Economic Journal: Applied Economics 2 (3):46–59.

Aziz, Abdul and Umma Naima. 2021. "Rethinking digital financial inclusion: Evidence from Bangladesh." Technology in Society 64:101509.

Barth, Erling, Sari Pekkala Kerr, and Claudia Olivetti. 2021. "The dynamics of gender earnings differentials: Evidence from establishment data." European Economic Review 134:103713.

Batista, Catia and Pedro C Vicente. 2023. "Is mobile money changing rural Africa? Evidence from a field experiment." Review of Economics and Statistics :1–29.

Beck, Thorsten, Haki Pamuk, Ravindra Ramrattan, and Burak R Uras. 2018. "Payment instruments, finance and development." Journal of Development Economics 133:162–186.

Bertrand, Marianne, Patricia Cortes, Claudia Olivetti, and Jessica Pan. 2021. "Social norms, labour market opportunities, and the marriage gap between skilled and unskilled women." The Review of Economic Studies 88 (4):1936–1978.

Boppart, Timo and Per Krusell. 2020. "Labor supply in the past, present, and future: a balanced-growth perspective." Journal of Political Economy 128 (1):118–157.

Carli, Francesco and Burak R Uras. 2024. "E-money, risk-Sharing, and welfare." European Economic Review :104832.

Chen, Boou and Chunkai Zhao. 2021. "Poverty reduction in rural China: Does the digital finance matter?" PLOS ONE 16 (12):1–27. URL https://doi.org/10.1371/journal.pone.0261214.

Chodorow-Reich, Gabriel, Gita Gopinath, Prachi Mishra, and Abhinav Narayanan. 2020. "Cash and the economy: Evidence from India's demonetization." The Quarterly Journal of Economics 135 (1):57–103.

Cole, Shawn, Mukta Joshi, and Antoinette Schoar. 2024. "Heuristics on Call: The Impact of Mobile-Phone-Based Business-Management Advice." The World Bank Economic Review 38 (3):580–597. URL https://doi.org/10.1093/wber/lhad038.

Cong, Lin William, Kay Giesecke, and Cami Kuhnen. 2024. "Call for Papers—Management Science Virtual Special Issue on Digital Finance." Management Science 70 (8):Vi–Vii.

Crouzet, Nicolas, Apoorv Gupta, and Filippo Mezzanotti. 2023. "Shocks and technology adoption: Evidence from electronic payment systems." Journal of Political Economy 131 (11):3003–3065.

Das, Satadru, Lucie Gadenne, Tushar Nandi, and Ross Warwick. 2023. "Does going cashless make you tax-rich? Evidence from India's demonetization experiment." Journal of Public Economics 224:104907.

De Mel, Suresh, Craig McIntosh, Ketki Sheth, and Christopher Woodruff. 2022. "Can mobile-linked bank accounts bolster savings? evidence from a randomized controlled trial in Sri Lanka." Review of Economics and Statistics 104 (2):306–320.

Demirguc-Kunt, Asli, Leora Klapper, Dorothe Singer, and Saniya Ansar. 2018. The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution. World Bank Publications.

Dubey, Tamanna Singh and Amiyatosh Purnanandam. 2023. "Can Cashless Payments Spur Economic Growth?" Available at SSRN 4373602 .

Duflo, Esther. 2012. "Women Empowerment and Economic Development." Journal of Economic Literature 50 (4):1051–1079.

D'Andrea, Angelo and Nicola Limodio. 2024. "High-speed internet, financial technology, and banking." Management Science 70 (2):773–798.

Exley, Christine L and Judd B Kessler. 2022. "The gender gap in self-promotion." The Quarterly Journal of Economics 137 (3):1345–1381.

Field, Erica, Rohini Pande, Natalia Rigol, Simone Schaner, and Charity Troyer Moore. 2021. "On her own account: How strengthening women's financial control impacts labor supply and gender norms." American Economic Review 111 (7):2342–2375.

Higgins, Sean. 2019. "Financial technology adoption." Northwestern University: Kellogg School of Management .

Insights, Fortune Business. 2023. "Digital Payment Market Size, Share Trends Analysis Report, 2023-2030." URL https://www.fortunebusinessinsights.com/digital-payment-market-102743. Accessed: 2024-09-12.

Jack, William and Tavneet Suri. 2014. "Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution." American Economic Review 104 (1):183–223.

Jayachandran, Seema. 2015. "The roots of gender inequality in developing countries." Annual Review of Economics 7 (1):63–88.

Kundu, Anirban. 2020. "Impact of trade liberalisation on formal–informal interlinkages in India: does sectoral labour mobility matter?" Journal of Economic Structures 9 (1):42.

Lewis, William Arthur et al. 1954. "Economic development with unlimited supplies of labour." .

Londoño-Vélez, Juliana and Pablo Querubin. 2022. "The impact of emergency cash assistance in a pandemic: Experimental evidence from Colombia." Review of Economics and Statistics 104 (1):157–165.

Mbiti, Isaac and David N Weil. 2015. "Mobile banking: The impact of M-Pesa in Kenya." In African successes, Volume III: Modernization and development. University of Chicago Press, 247–293.

Moorena, Lolita, Mikaela Rabb, Aliyyah Rusdinar, Simone Schaner, Caroline Tangoren, and Natalie Theys. 2020. "Towards inclusive digital finance in indonesia." Inclusive Financial Innovation Initiative (IFII) White Paper .

Pazarbasioglu, Ceyla, Alfonso Garcia Mora, Mahesh Uttamchandani, Harish Natarajan, Erik Feyen, and Mathew Saal. 2020. "Digital financial services." World Bank 54:1–54.

Riley, Emma. 2018. "Mobile money and risk sharing against village shocks." Journal of Development Economics 135:43–58.

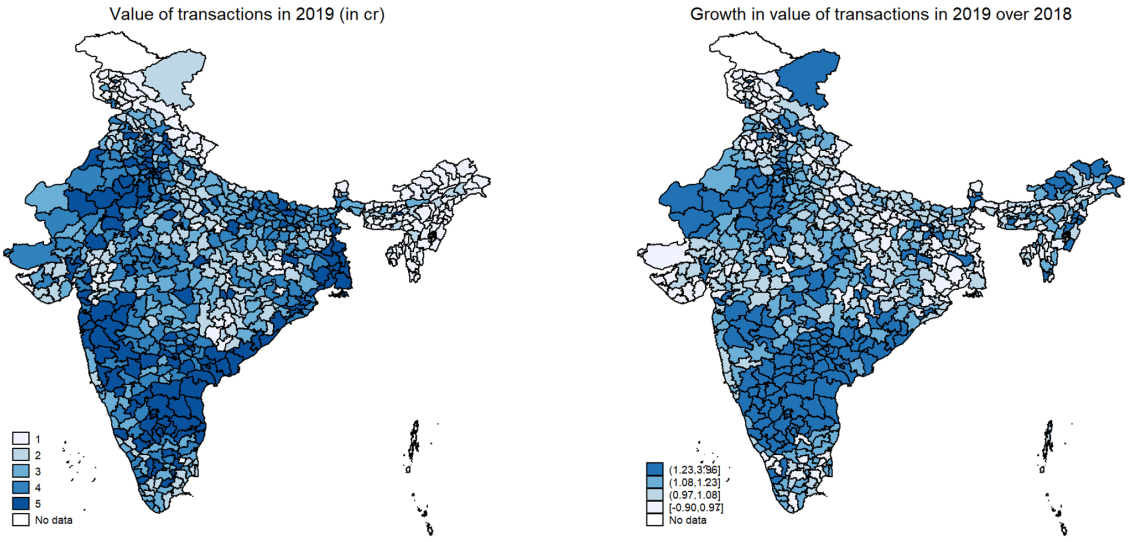
Shapiro, Alan Finkelstein and Federico S Mandelman. 2021. "Digital adoption, automation, and labor markets in developing countries." Journal of Development Economics 151:102656.

Statista. 2023. "Digital Payments Worldwide - Statistics Facts." URL https://www.statista.com/statistics/871273/worldwide-digital-payments-market-size/. Accessed: 2024-09-12.

Suri, Tavneet, Prashant Bharadwaj, and William Jack. 2021. "Fintech and household resilience to shocks: Evidence from digital loans in Kenya." Journal of Development Economics 153:102697.

Suri, Tavneet and William Jack. 2016. "The long-run poverty and gender impacts of mobile money." Science 354 (6317):1288–1292.

7 Tables and Figures



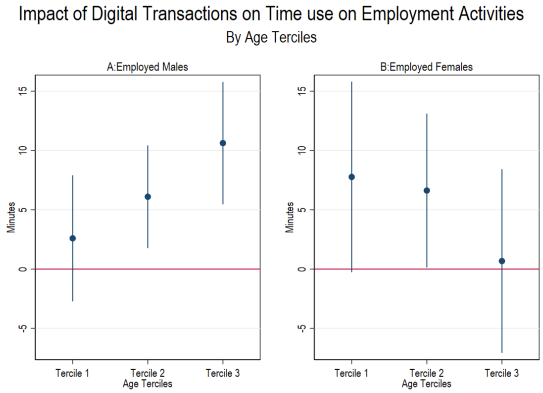
(a) DFS Transaction in 2019 (in Quintiles of Crores

(b) Growth of DFS Transactions Between 2018 over 2019

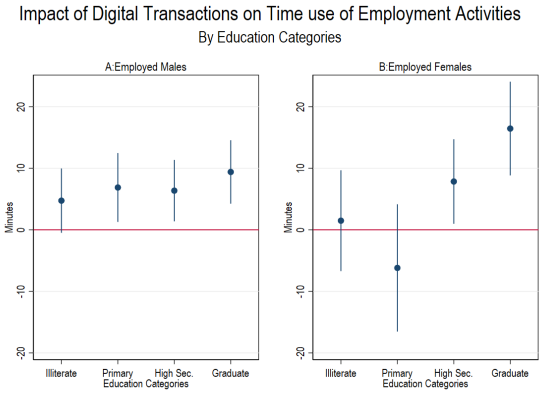
Figure 1: District-level maps of UPI usage. Panel (a) shows the the five quintiles of averages of DFS for 2019. Panel (b) shows the growth rates of DFS. -0.90 to 0.97 meaning the districts for which the range of growth of DFS is between -90% and 97% between 2018 and 2019.



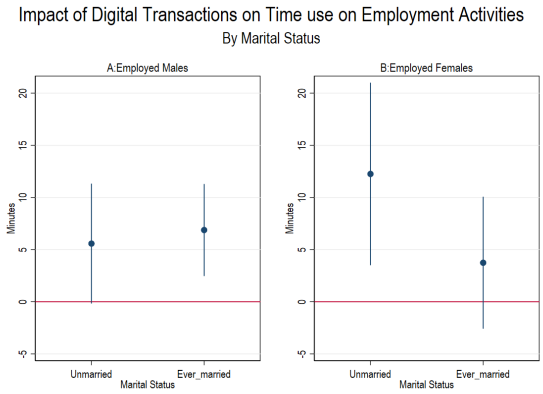
Figure 2: Impact of DFS on Employment by Sector. This figure presents the effect of digital transactions on employment outcomes, disaggregated by gender and sector (rural/urban), across various employment categories. The y-axis represents the percentage point change in employment outcomes, and the x-axis shows the sector (rural or urban). The blue points indicate the estimated coefficients, while the vertical lines represent 95% confidence intervals. Each panel corresponds to a specific employment category: self-employed, unpaid self-employed, and regular wage employment for both men and women.



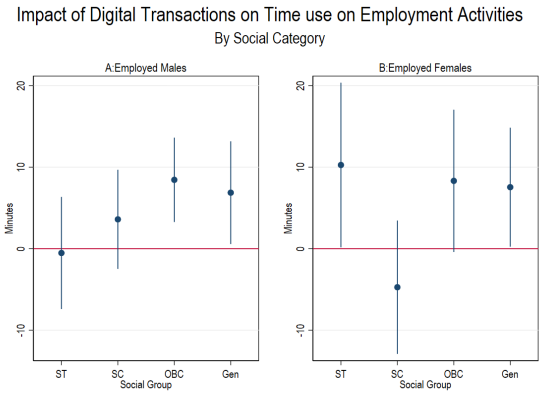
(a) Heterogeneity by age terciles



(b) Heterogeneity by education categories



(c) Heterogeneity by marital status



(d) Heterogeneity by social groups

Figure 3: Heterogeneity analysis of the intensive margin of time use in employment activities, disaggregated by demographic factors. Panel (a) examines the impact by age terciles, showing differences in the effect of digital transactions on time use for employed males and females across different age groups. Panel (b) focuses on education categories, revealing how educational attainment influences the effect on employment time. Panel (c) analyzes the impact by marital status, comparing unmarried and ever-married individuals, and Panel (d) explores heterogeneity by social groups (ST, SC, OBC, and General), highlighting the variation across caste categories. The y-axis in each panel represents the effect of digital transactions on time spent in minutes, while the x-axis denotes different demographic categories. The points represent coefficient estimates, with the vertical lines depicting 95% confidence intervals.

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
	Males			Females			Difference in Mean	
	N	Mean	SD	N	Mean	SD		
A. PLFS 2019-2020								
	Extensive Margin							
Employed	96,491	0.71	0.46	68,465	0.18	0.38	0.53	***
- Employed in Agriculture	96,491	0.24	0.42	68,465	0.07	0.26	0.16	***
- Employed in Non-agriculture	96,491	0.47	0.50	68,465	0.10	0.31	0.37	***
Self Employed	96,491	0.36	0.48	68,465	0.07	0.25	0.29	***
- Self-employed in Agriculture	96,491	0.18	0.38	68,465	0.04	0.19	0.14	***
- Self-employed in Non-agriculture	96,491	0.18	0.38	68,465	0.03	0.17	0.15	***
Unpaid Self Employed	96,491	0.04	0.19	68,465	0.06	0.24	-0.03	***
Regular Employed	96,491	0.19	0.39	68,465	0.06	0.001	0.13	***
Casual Employed	96,491	0.16	0.36	68,465	0.05	0.22	0.11	***
	Intensive Margin							
Wages for self-employment activities	34,640	10853	9924.2	4494	5013	6079.6	5839.9	***
Wages for Regular salary/wage activities	33,520	9402.1	15213.4	7768	7097.2	13244.9	2304.8	***
B. TUS Data 2019-2020								
	Intensive Margin							
Time spent on Paid Activities (In minutes)								
Employed	82,444	414.06	112.55	16,535	344.54	116.28	69.52	***
Self Employed	35,763	395.77	126.54	4,465	307.46	127.47	88.31	***
Regular Employed	21,087	442.59	97.80	5,353	365.07	111.99	77.52	***
Casual Employed	25,594	416.10	96.99	6,717	352.83	105.69	63.27	***
Time spent on Other Activities for employed persons (In minutes)								
Unpaid Activities	82444	45.902	71.967	16535	227.333	130.989	-181.43	***
Learning, Social & Cultural	82444	202.573	112.107	16535	159.39	97.29	43.19	***
Self-Care	82444	700.81	87.21	16535	660.70	82.47	40.10	***
C. NFHS								
Own Bank account	45,626	0.854	0.352	53,117	0.775	0.417	0.079	***
Own Mobile	45,626	0.905	0.293	53,117	0.532	0.498	0.372	***
Used Internet	45,626	0.515	0.499	53,117	0.294	0.456	0.221	***
Use mobile for financial transaction	41,296	0.246	0.431	28,284	0.202	0.401	0.045	***
Financial Autonomy				53,117	0.493	0.499		

Notes: This table presents summary statistics for both males and females, comparing various employment measures across agricultural and non-agricultural sectors. Columns (1)-(3) report statistics for males, while columns (4)-(6) correspond to females. Column (7) highlights the difference in means between males and females, with significance levels denoted by *** ($p < 0.01$). Employment measures cover the extensive margin (i.e., whether the individual is employed in agriculture, non-agriculture, self-employment, or unpaid self-employment) and the intensive margin (i.e., wages for employment activities, time spent on paid activities, and time spent on other activities such as unpaid work and self-care). The intensive margin includes data from the Time Use Survey (TUS) 2019-2020, and the extensive margin is derived from the Periodic Labour Force Survey (PLFS) 2019-2020. The last section incorporates financial autonomy measures from the National Family Health Survey (NFHS). Standard deviations (SD) are reported in parentheses, and differences between males and females are statistically tested, with significance levels marked as * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

Table 2: Impact of Digital Economy on Employment Structure (2SLS) using PLFS data: Extensive Margin

	Type of employment dummy (2SLS)			
	(1)	(2)	(3)	(4)
	All Employment	Self-Employment	Regular Employment	Casual Employment
	Panel A: Males			
Amount (log)	0.000	-0.037***	0.048***	-0.011**
SE	[0.005]	[0.007]	[0.007]	[0.005]
P-val	[0.978]	[0.000]	[0.000]	[0.048]
N	96491	96491	96491	96491
F-stat from first stage	63.741	63.741	63.741	63.741
Sample Mean	0.743	0.358	0.190	0.156
	Panel B: Females			
Amount (log)	0.004	-0.002	0.016***	-0.010***
SE	[0.006]	[0.005]	[0.003]	[0.003]
P-val	[0.488]	[0.721]	[0.000]	[0.002]
N	68465	68465	68465	68465
F-stat from first stage	66.95	66.95	66.95	66.95
Sample Mean	0.242	0.065	0.063	0.05
Z-score	0.512	4.068***	4.201***	0.171

Notes: (i) These models estimate the impact of digital transactions on the incidence of employment by gender. (ii) The dependant variable in each model is a dummy variable. In column (1), if a person is employed as per the Usual Principal Activity Status, the dummy takes value '1'. It takes value '0' for those who are unpaid self-employed, unemployed or out of labour force. (iii) Self-employment dummy takes value '1' if a person is self-employed (own-account worker or employer), '0' otherwise. Similarly, the regular and casual wage dummies are defined. (iv) The main explanatory variable in all models is the district-level amount transacted via digital platform of Phonepay. It is computed as an average of value of transactions for the years of 2018 and 2019. (v) All models are estimated on the basis of 2SLS model, where the main explanatory variable is instrumented by the district-level exposure to the bank chests. Standard deviations (SD) are reported in parentheses, and differences between males and females are statistically tested, with significance levels marked as * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

Table 3: Impact of Digital Economy on Employment in Agricultural and Non-Agricultural Sector

	(1) Agricultural Employment	(2) Non-agricultural Employment	(3) Agricultural Self-Employment	(4) Non-agricultural Self-Employment	(5) Unpaid Self-Employment
	Panel A: Males				
Amount (log)	-0.077***	0.077***	-0.064***	0.027***	-0.009***
SE	[0.008]	[0.009]	[0.008]	[0.006]	[0.002]
P-val	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
N	96491	96491	96491	96491	96491
F-stat from first stage	63.741	63.741	63.741	63.741	63.741
Sample Mean	0.235	0.470	0.180	0.178	0.037
	Panel B: Females				
Amount (log)	-0.017***	0.021***	-0.007*	0.005	-0.022***
SE	[0.005]	[0.005]	[0.004]	[0.003]	[0.005]
P-val	[0.000]	[0.000]	[0.063]	[0.109]	[0.000]
N	68465	68465	68465	68465	68465
F-stat from first stage	66.95	66.95	66.95	66.95	66.95
Sample Mean	0.074	0.104	0.036	0.029	0.063
Z-score	6.360***	5.439***	6.373***	3.279***	2.414**

Note: This table shows the impact of the digital economy on employment outcomes in agricultural and non-agricultural sectors, with a focus on self-employment. Columns (1) and (2) report the effects on agricultural and non-agricultural employment, while columns (3) through (5) analyze self-employment, differentiating between agricultural, non-agricultural, and unpaid self-employment. Agricultural self-employment captures activities related to farming and allied sectors, while non-agricultural self-employment covers informal businesses and entrepreneurial activities. Unpaid self-employment refers to those engaged in family-owned enterprises without direct wages. Standard errors are clustered and presented in brackets. The Z-score tests for significant gender differences in the coefficients across employment types. Control variables include individual and household characteristics. F-statistics from the first-stage regression are reported for robustness. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is drawn from the PLFS 2019-2020 dataset.

Table 4: Impact of digital transactions on time spent on paid activities: Intensive Margin

2SLS and Control Variables				
	(1) Any employment	(2) Self-employed	(3) Regular wage	(4) Casual/other wage
	Panel A: Males			
Amount (log)	6.662**	8.632***	4.635*	-4.278
SE	[2.674]	[3.038]	[2.652]	[3.644]
P-value	[0.013]	[0.004]	[0.080]	[0.240]
N	82444	35763	21087	25594
F-stat from first stage	76.27	85.169	38.787	101.913
Sample Mean	414.06	396	443	416
Controls	Yes	Yes	Yes	Yes
	Panel B: Females			
Amount (log)	5.219	10.606*	7.955**	-0.666
SE	[3.587]	[5.794]	[3.291]	[6.637]
P-value	[0.146]	[0.067]	[0.016]	[0.920]
N	16535	4465	5353	6717
F-stat from first stage	61.780	77.076	42.904	44.935
Sample Mean	344.54	307	365	353
Controls	Yes	Yes	Yes	Yes
Z-Score	0.323	0.302	0.785	0.653

Notes: (i) These models estimate the impact of digital transactions on the time spent on productive activities for males. (ii) Analysis is conducted separately for those who are employed in any category, self-employed, regular-wage employed and casual/other wage employed. (iii) The dependant variable in each model is the sum of time spent on Employment in corporations, government and non-profit institutions; Employment in household enterprises to produce goods; and Employment in household enterprises to provide services. (iv) The main explanatory variable in all models is the district level amount transacted via digital platform of Phonepay. It is computed as an average of value of transactions for the years of 2018 and 2019. (v) All the models are estimated using 2SLS model and include control variables. (vi) The main explanatory variable (amount) is instrumented by the district level exposure to the bank chests. (vii) Robust standard errors are clustered at the district level and given in the parentheses. (viii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Impact of digital transactions on time spent on other (unpaid) activities for employed in any category

	(1)	(2)	(3)
	Unpaid Activities	Learning, Social and Cultural	Self-Care
	Panel A: Employed Men		
Amount(log)	-3.883***	-0.456	-5.766***
SE	[1.214]	[2.685]	[2.188]
P-value	[0.001]	[0.865]	[0.008]
N	82444	82444	82444
F-stat from first stage	76.27	76.27	76.27
Sample Mean	45.90	202.57	700.81
Controls	Yes	Yes	Yes
	Panel B: Employed Women		
Amount(log)	-9.095**	9.348***	-5.258*
SE	[3.552]	[3.088]	[2.791]
P-value	[0.010]	[0.002]	[0.060]
N	16535	16535	16535
F-stat from first stage	61.78	61.78	61.78
Sample Mean	227.33	159.39	660.70
Controls	Yes	Yes	Yes
Z-Score	1.388	2.396**	0.143

Notes: (i) These models estimate the impact of digital transactions on the time spent on other (unpaid) activities by gender. (ii) Analysis is conducted for those who are employed in any category. (iii) The dependent variable in column (1) is the sum of time spent on Production of goods for own final use; Unpaid domestic and caregiving services for household members; and Unpaid volunteer, trainee and other unpaid work. The dependent variable in column (2) is the sum of time spent on Learning and Socializing and communication, community participation and religious practice; and time spent on Culture, leisure, mass media and sports practices. The dependent variable in column (3) is the time spent on self-care. (iv) The main explanatory variable in all models is the district-level amount transacted via digital platform of Phonepay. It is computed as an average of value of transactions for the years of 2018 and 2019. (v) All the models are estimated using the 2SLS model where the main explanatory variable (amount) is instrumented by the district-level exposure to the bank chests. (vi) The control variables are included in all the models. (vii) Robust standard errors are clustered at the district level and given in parentheses. (viii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Impact on Wages (2SLS) using PLFS: Intensive Margin

	Earnings from self-employment activity		Earnings for Regular Employed	
	(1) Male	(2) Female	(3) Male	(4) Female
Amount (log)	1108.24***	629.06*	1235.9***	1140.7***
SE	[253.7]	[336.7]	[293.8]	[390.1]
P-val	[0.000]	[0.062]	[0.000]	[0.003]
N	34640	4494	33520	7768
F-stat from first stage	70.3	33.6	54.8	44.8
Sample Mean	10853	5013	9402	7097
Z-Score	1.136		0.194	

Notes: (i) These models estimate the impact of digital transactions on the average wage. (ii) The dependent variable in models (1 2) and (34) is gross earning for last 30 days from self-employment activity; and earning during the preceding calendar month for regular salaried/wage activity respectively. (iii) Models 1 2 are estimated for those who are self-employed. Models 3 4 are estimated for those who are working in any type of wage labour. (iv) The main explanatory variable in all models is the district-level amount transacted via digital platform of Phonepay. It is computed as an average of value of transactions for the years of 2018 and 2019. (v) All models are estimated on the basis of 2SLS model, where the main explanatory variable is instrumented by the district level exposure to the bank chests. (vi) Robust standard errors are clustered at the district level and given in the parentheses. (vii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Impact of digital transactions on NFHS indicators: 2SLS Estimation

	(1) Owning a bank account	(2) Owning a phone	(3) Using mobile for financial transactions	(4) Use of internet	(5) Money that you can yourself use
	Panel A: Males				
Amount (log)	0.029***	0.008	0.039***	0.067***	
SE	[0.010]	[0.006]	[0.014]	[0.014]	
P-val	[0.004]	[0.219]	[0.005]	[0.000]	
N	45,626	45,626	41,296	45,626	
F-stat from first stage	33.666	33.666	32.467	33.666	
Sample Mean	0.854	0.905	0.246	0.515	
	Panel B: Females				
Amount (log)	0.022**	0.067***	0.027*	0.079***	0.046***
SE	[0.009]	[0.015]	[0.016]	[0.014]	[0.014]
P-val	[0.017]	[0.000]	[0.090]	[0.000]	[0.001]
N	53,117	53,117	28,284	53,117	53,117
F-stat from first stage	36.446	36.446	26.891	36.45	36.446
Sample Mean	0.775	0.532	0.401	0.456	0.499
Z-Score	0.520	3.652***	0.564	0.606	

Notes: (i) These models estimate the impact of average value of digital transactions on five indicators namely: owning a mobile; owning a phone; using phone for financial transactions; use of internet; and money that the women can herself use. (ii) All these dependant variables are in the form of dummy variables where 'yes; is coded as '1' and 'no' as '0'. (iii) The main explanatory variable in all models is the district-level average amount transacted via digital platform of Phonepay. It is computed as average of value transacted in 2018 and 2019. (iv) All models are estimated using 2SLS model and include control variables. (v) The main explanatory variable (growth in amount) is instrumented by the district level exposure to the bank chests. (vi) Robust standard errors are clustered at the district level and given in the parentheses. (vii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. (viii) Date source: NFHS and Phonepay.

Online Appendix

A0.1 Robustness Tables

Table A1: Additional Summary Statistics

Panel A: Additional summary statistics from TUS data								
	Males			Females			Difference in Mean	
	N	Mean	SD	N	Mean	SD		
	Extensive Margin							
Employed	1,51,696	0.703	0.457	1,50,196	0.153	0.359	0.550	***
Self Employed	1,51,696	0.321	0.467	1,50,196	0.045	0.207	0.276	***
Regular Employed	1,51,696	0.170	0.376	1,50,196	0.047	0.211	0.123	***
Casual Employed	1,51,696	0.212	0.409	1,50,196	0.061	0.239	0.151	***
	Intensive Margin							
Production of goods								
Employed	82,444	184.27	197.03	16,535	170.32	180.12	13.95	***
Self Employed	35,763	188.32	188.09	4,465	180.20	162.92	8.12	***
Regular Employed	21,087	66.47	153.35	5,353	41.75	120.68	24.71	***
Casual Employed	25,594	275.68	190.87	6,717	266.22	167.87	9.45	***
Production of Services								
Employed	82,444	132.24	194.20	16,535	76.98	149.83	55.26	***
Self Employed	35,763	166.87	203.77	4,465	104.06	162.60	62.80	***
Regular Employed	21,087	128.07	194.32	5,353	100.67	166.89	27.40	***
Casual Employed	25,594	87.30	169.26	6,717	40.10	114.89	47.20	***

Panel B: Summary Statistics for DFS and Banking at the District Level							
	N	Mean	SD	Min	25th	75th	Max
Amount (log)	512	21.59	1.18	16.45	20.81	22.24	26.53
Count (log)	512	14.16	1.24	8.76	13.37	14.82	19.41
Growth in amount of transactions	512	1.107	0.29	-0.90	0.98	1.22	2.53
Chest Exposure Index	512	0.55	0.19	0.11	0.15 Status ATM	512	0.031 0.07
0	0.004	0.03	0.5				
Status Commercial Banks	512	0.08	0.13	0	0.027	0.08	0.85

Notes: Panel A presents additional summary statistics from the Time Use Survey (TUS) 2019-2020 data, disaggregated by gender, focusing on both extensive and intensive margins. The extensive margin reports the proportion of individuals employed, self-employed, and working in regular or casual employment. The intensive margin covers time spent on production of goods and services, highlighting gender differences in hours worked across employment types. Panel B provides summary statistics for outcome and control variables related to financial transactions, including the amount and growth of transactions, as well as the availability of ATMs and commercial banks. Differences in means between males and females are tested, with significance levels denoted by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$). All statistics are presented with their corresponding sample sizes (N), means, standard deviations (SD), and range (Min, Max, 25th, 75th percentiles) where applicable.

Table A2: Impact of growth in value of digital transactions on NFHS indicators: Post-Covid

	(1)	(2)	(3)	(4)	(5)
	Owning a bank account	Owning a phone	Using mobile for financial transactions	Use of internet	Money that you can yourself use
Panel A: Male					
Growth in amount (2021 over 2018)	-0.077	0.015	0.496	0.671	
SE	[0.135]	[0.093]	[0.435]	[0.530]	
P-val	[0.568]	[0.875]	[0.254]	[0.205]	
N	24,389	24,389	21464	24389	
F-stat from first stage	1.98	1.985	2.199	1.98	
Panel B: Female					
Growth in amount (2021 over 2018)	0.047	0.766	0.36*	0.806	0.111
SE	[0.143]	[0.529]	[0.203]	[0.545]	[0.234]
P-val	[0.743]	[0.148]	[0.076]	[0.140]	[0.637]
N	26,842	26,842	13,077	26,842	26,842
F-stat from first stage	2.587	2.587	3.442	2.59	2.587

Note: This table presents the impact of growth in the value of digital transactions on key National Family Health Survey (NFHS) indicators in the post-COVID period, 2021, estimated using the 2SLS model. The dependent variables include ownership of a bank account, ownership of a phone, use of mobile phones for financial transactions, internet usage, and access to money for personal use. Panel A shows results for males, and Panel B for females. The main independent variable is the growth in the value of digital transactions from 2018 to 2021. Standard errors (SE) are reported in brackets, with p-values provided for each estimate. Significance levels are denoted by *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.10$). All regressions include individual and household controls. The F-statistic from the first stage of the instrumental variable regression is reported to indicate the strength of the instrument. Sample sizes (N) reflect the number of observations used for each regression.

Table A3: Division of time spent on production of goods and services: 2SLS Model

	(1) Any employment	(2) Self Employed	(3) Regular Wage	(4) Casual Wage
Panel A: Male				
	Dependent Variable: Time spent on production of goods			
Amount (log)	-17.935***	-18.487***	5.523	-12.529*
SE	[4.738]	[5.191]	[4.761]	[6.587]
P-value	[0.000]	[0.000]	[0.246]	[0.057]
N	82444	35763	21087	25594
F-stat from first stage	76.267	85.169	38.79	101.913
Sample Mean	184	188	66	276
Controls	Yes	Yes	Yes	Yes
	Dependent Variable: Time spent on production of services			
Amount (log)	13.459***	20.878***	10.3	5.626
SE	[4.849]	[6.063]	[9.563]	[5.173]
P-value	[0.006]	[0.001]	[0.281]	[0.277]
N	82444	35763	21087	25594
F-stat from first stage	76.267	85.17	38.79	101.91
Sample Mean	132	167	128	87
Controls	Yes	Yes	Yes	Yes
Panel B: Female				
	Dependent Variable: Time spent on production of goods			
Amount (log)	-12.467**	1.487	9.843*	-8.421
SE	[5.939]	[6.681]	[5.104]	[10.042]
P-value	[0.036]	[0.824]	[0.054]	[0.402]
N	16535	4465	5353	6717
F-stat from first stage	61.776	77.08	42.9	44.94
Sample Mean	170	180	42	266
Controls	Yes	Yes	Yes	Yes
	Dependent Variable: Time spent on production of services			
Amount (log)	20.829***	9.481	20.195**	14.778**
SE	[5.137]	[6.244]	[8.882]	[6.183]
P-value	[0.000]	[0.129]	[0.023]	[0.017]
N	16535	4465	5353	6717
F-stat from first stage	61.776	77.08	42.90	44.94
Sample Mean	77	104	101	40
Controls	Yes	Yes	Yes	Yes

Notes: (i) These models estimate the impact of digital transactions on the time spent on production of goods and services. (ii) Analysis is conducted separately for those who are employed in any category, self-employed, regular-wage employed and casual/other-wage employed. (iii) The dependent variable in Section 1 2 is time spent on Employment in household enterprises to produce goods; and Employment in household enterprises to provide services respectively. (iv) The main explanatory variable in all models is the district-level amount transacted via digital platform of Phonepay. It is computed as an average of value of transactions for the years of 2018 and 2019. (v) All the models are estimated using 2SLS model and include control variables. (vi) The main explanatory variable (amount) is instrumented by the district-level exposure to the bank chests. (vii) Robust standard errors are clustered at the district level and given in the parentheses. (viii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A4: Impact of digital transactions on time spent on other (unpaid) activities (2SLS): By Employment Category

	(1) Unpaid Activities	(2) Learning, Social and Cultural	(3) Self-Care
Panel A1: Self-employed men			
Amount(log)	-4.974**	-0.546	-6.752***
SE	[1.950]	[3.221]	[2.302]
P-value	[0.011]	[0.865]	[0.003]
N	35763	35763	35763
F-stat from first stage	85.169	85.169	85.169
Sample Mean	53	217	708
Panel A2: Regular wage-employed men			
Amount(log)	-2.037*	-1.95	-2.83
SE	[1.169]	[3.037]	[2.724]
P-value	[0.081]	[0.521]	[0.299]
N	21087	21087	21087
F-stat from first stage	38.787	38.787	38.787
Sample Mean	35	190	675
Panel B1: Self-employed women			
Amount(log)	-7.353	9.612**	-10.709***
SE	[4.621]	[4.750]	[3.414]
P-value	[0.112]	[0.043]	[0.002]
N	4465	4465	4465
F-stat from first stage	77.076	77.076	77.076
Sample Mean	264	177	670
Panel B2: Regular wage-employed women			
Amount(log)	-12.062***	3.314	1.233
SE	[3.719]	[3.286]	[3.134]
P-value	[0.001]	[0.313]	[0.694]
N	5353	5353	5353
F-stat from first stage	42.904	42.904	42.904
Sample Mean	195	165	648

Notes: This table presents the impact of digital transactions on time spent on unpaid activities, learning/social/cultural activities, and self-care, estimated using a 2SLS model. The analysis is broken down by employment category, including self-employed and regular wage-employed individuals, with results separately reported for men (Panels A1 and A2) and women (Panels B1 and B2). The main independent variable is the log of digital transactions, and the dependent variables reflect the time spent on each activity category (in minutes). Standard errors (SE) are reported in brackets, and p-values indicate the significance of the estimates. Significance levels are denoted by *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.10$). All regressions include individual and household controls, and the F-statistics from the first stage are provided to assess the strength of the instrumental variable. Sample means indicate the average time spent on each activity for the corresponding employment category. The sample sizes (N) reflect the number of observations used in each regression.

Table A5: Extensive Margin for Types of Employment Dummies OLS Model) (PLFS)

	(1) All employment	(2) Agricultural Employment	(3) Non-agricultural Employment	(4) Self-employment	(5) Agricultural Self-employment	(6) Non-agricultural Self-employment	(7) Unpaid Self-employment	(8) Regular employment	(9) Casual Employment
					Panel A: Men				
Amount(log)	-0.003	-0.061***	0.058***	-0.037***	-0.052***	0.014***	-0.009***	0.047***	-0.013***
SE	[0.002]	[0.005]	[0.005]	[0.004]	[0.004]	[0.002]	[0.001]	[0.005]	[0.003]
P-value	[0.203]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
N	96491	96491	96491	96491	96491	96491	96491	96491	96491
Sample Mean	0.706	0.235	0.47	0.358	0.18	0.178	0.037	0.19	0.156
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
					Panel B: Women				
Amount(log)	0.002	-0.018***	0.020***	-0.008***	-0.010***	0.003*	-0.017***	0.017***	-0.007***
SE	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]	[0.001]	[0.003]	[0.002]	[0.002]
P-value	[0.379]	[0.000]	[0.000]	[0.000]	[0.000]	[0.013]	[0.000]	[0.000]	[0.000]
N	68465	68465	68465	68465	68465	68465	68465	68465	68465
Sample Mean	0.179	0.074	0.104	0.065	0.036	0.029	0.063	0.063	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (i) These models estimate the impact of digital transactions on the incidence of employment by gender. (ii) The dependant variable in each model is a dummy variable. In column (1), if a person is employed as per the Usual Principal Activity Status, the dummy takes value '1'. It takes value '0' for those who are unpaid self-employed, unemployed or out of labour force. (iii) Self-employment dummy takes value '1' if a person is self-employed (own-account worker or employer), '0' otherwise. Similarly, the regular and casual wage dummies are defined. (iv) The main explanatory variable in all models of Panel B is the district level amount transacted via digital platform of Phonepay. It is computed as an average of value of transactions for the years of 2018 and 2019. (v) All models are estimated on the basis of 2SLS model, where the main explanatory variable is instrumented by the district level exposure to the bank chests. (vi) Robust standard errors are clustered at the district level and given in the parentheses. (vii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A6: Impact of digital transactions on time spent on paid activities: Intensive Margin (OLS Model)

	(1) All employment	(2) Self-employment	(3) Regular employment	(4) Casual employment
Panel A: Male				
Amount (log)	8.368***	9.316***	4.816***	2.34
SE	[1.502]	[1.671]	[1.287]	[1.737]
P-value	[0.000]	[0.000]	[0.000]	[0.179]
N	82444	35763	21087	25594
Controls	Yes	Yes	Yes	Yes
Sample Mean	414	396	443	416
Panel B: Female				
Amount (log)	6.252***	7.671**	10.657***	-2.244
SE	[1.729]	[3.325]	[1.669]	[2.630]
P-value	[0.000]	[0.022]	[0.000]	[0.394]
N	16,535	4465	5353	6717
Controls	Yes	Yes	Yes	Yes
Sample Mean	344	307	365	353

Note: This table presents the impact of digital transactions on time spent on paid activities, estimated using an Ordinary Least Squares (OLS) model. The dependent variable is the time spent (in minutes) on different forms of paid employment, including all employment, self-employment, regular employment, and casual employment. The time spent is conditional on individuals spending more than zero minutes on the respective employment type, hence focusing on the intensive margin. Panel A shows results for males, and Panel B for females. The main independent variable is the log of digital transactions, and standard errors (SE) are reported in brackets. The table reports p-values for each estimate, with significance levels denoted by *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.10$). Sample means refer to the average time spent on each employment type. All regressions include controls for individual and household characteristics, with sample sizes (N) specified for each employment type.

Table A7: Impact of digital transactions on time spent on paid activities in intensive margin: Alternate explanatory variable

Explanatory variable: Count of digital transactions				
	(1) Any employment	(2) Self Employed	(3) Regular Wage	(4) Casual Wage
	Panel A: Men			
Count (log)	6.613**	8.576***	4.658*	-4.194
SE	[2.669]	[3.020]	[2.685]	[3.562]
P-value	[0.013]	[0.005]	[0.083]	[0.239]
N	82444	35763	21087	25594
F-stat from first stage	72.091	81.219	34.451	104.525
Sample Mean	414	396	443	416
Controls	Yes	Yes	Yes	Yes
	Panel B: Women			
Count (log)	5.134	10.415*	8.023**	-0.641
SE	[3.522]	[5.695]	[3.304]	[6.382]
P-value	[0.145]	[0.067]	[0.015]	[0.920]
N	16535	4465	5353	6717
F-stat from first stage	59.08	76.25	38.026	47.193
Sample Mean	345	307	365	353
Controls	Yes	Yes	Yes	Yes

Notes: (i) These models estimate the impact of digital transactions on the time spent on productive activities for males. (ii) Analysis is conducted separately for those who are employed in any category, self-employed, regular-wage employed and casual-wage employed. (iii) The dependent variable in each model is the sum of time spent on Employment in corporations, government and non-profit institutions; Employment in household enterprises to produce goods; and Employment in household enterprises to provide services. (iv) The main explanatory variable in all models is the district-level number of transactions via digital platform of Phonepay. It is computed as an average of count of transactions for the years of 2018 and 2019. (v) All the models are estimated using 2SLS model and include control variables. (vi) The main explanatory variable (count) is instrumented by the district-level exposure to the bank chests. (vii) Robust standard errors are clustered at the district level and given in the parentheses. (viii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A8: Impact of growth in amount transacted on time spent on productive activities: 2SLS

Dependent variable: Time spent on productive activities				
	(1) Any employment	(2) Self employed	(3) Regular wage	(4) Casual Wage
Panel A: Male				
Growth in amount (2019 over 2018)	41.812**	55.480**	24.993	-29.079
SE	[19.518]	[21.976]	[15.724]	[24.721]
P-value	[0.032]	[0.012]	[0.112]	[0.239]
N	82444	35763	21087	25594
F-stat from first stage	23.632	23.05	24.573	18.106
Sample Mean	414	396	443	416
Controls	Yes	Yes	Yes	Yes
Panel B: Female				
Growth in amount (2019 over 2018)	36.074	77.399*	40.635**	-6.554
SE	[25.236]	[46.141]	[17.069]	[65.448]
P-value	[0.153]	[0.093]	[0.017]	[0.920]
N	16535	4465	5353	6717
F-stat from first stage	26.461	23.779	33.353	11.997
Sample Mean	345	307	365	353
Controls	Yes	Yes	Yes	Yes

Notes: (i) These models estimate the impact of growth in digital transactions on the time spent on productive activities separately for males (Panel A) and females (Panel B). (ii) Analysis is conducted separately for those who are in any type of employment, self-employment, regular-wage and casual/other wage employment. (iii) The dependent variable in each model is the sum of time spent on Employment in corporations, government and non-profit institutions; Employment in household enterprises to produce goods; and Employment in household enterprises to provide services. (iv) The main explanatory variable in all models is the growth in district-level amount transacted via digital platform of Phonepay. It is computed as growth in the value of transactions in 2019 over 2018. (vi) All models are estimated using 2SLS model and include control variables. (vii) The main explanatory variable (growth in amount) is instrumented by the district-level exposure to the bank chests. (viii) Robust standard errors are clustered at the district level and given in the parentheses. (ix) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A9: Impact of Digital Economy on Employment Structure (2SLS): Extensive Margin (ITUS)

	(1) All employment	(2) Self-employment	(3) Regular employment	(4) Casual employment
Panel A: Male				
Amount (log)	-0.008**	-0.039***	0.036***	-0.006
SE	[0.004]	[0.006]	[0.007]	[0.005]
P-value	[0.044]	[0.000]	[0.000]	[0.274]
N	151696	151696	151696	151696
F-stat from first stage	81.394	81.394	81.394	81.394
Controls	Yes	Yes	Yes	Yes
Sample Mean	0.703	0.32	0.17	0.211
Panel B: Female				
Amount (log)	0.003	0.001	0.009***	-0.007*
SE	[0.005]	[0.002]	[0.002]	[0.004]
P-value	[0.488]	[0.629]	[0.000]	[0.097]
N	150196	150196	150196	150196
F-stat from first stage	85.15	85.15	85.15	85.15
Controls	Yes	Yes	Yes	Yes
Sample Mean	0.152	0.044	0.046	0.06

Notes: This table presents the impact of the digital economy on employment structure, using two-stage least squares (2SLS) estimation from the India Time Use Survey, 2019. The dependent variables cover various forms of employment on the extensive margin, including all employment, self-employment, regular employment, and casual employment. Panel A reports results for males, and Panel B for females. The main independent variable is the log of the amount of digital transactions, with standard errors (SE) reported in brackets and clustered at the individual level. P-values are provided to indicate the statistical significance of the estimates, with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The F-statistic from the first stage is reported to assess the strength of the instrumental variable, and all regressions include controls for individual and household characteristics. Sample means indicate the proportion of individuals in each employment category.

Table A10: Impact of growth in value of digital transactions on NFHS indicators: Pre-Covid

	(1)	(2)	(3)	(4)	(5)
	Owning a bank account	Owning a phone	Using mobile for financial transactions	Use of internet	Money that you can yourself use
Panel A: Male					
Growth in amount (2019 over 2018)	0.176**	0.046	0.234**	0.413***	
SE	[0.071]	[0.039]	[0.097]	[0.121]	
P-val	[0.013]	[0.238]	[0.016]	[0.001]	
N	45,626	45,626	41,296	45,626	
F-stat from first stage	14.92	14.92	14.983	14.92	
Panel B: Female					
Growth in amount (2019 over 2018)	0.137**	0.413***	0.138	0.486***	0.285***
SE	[0.064]	[0.129]	[0.084]	[0.133]	[0.103]
P-val	[0.034]	[0.001]	[0.102]	[0.000]	[0.006]
N	53,117	53,117	28,284	53,117	53,117
F-stat from first stage	14.576	14.576	14.377	14.58	14.576

Notes: This table presents the impact of growth in the value of digital transactions on key National Family Health Survey (NFHS, 2019-2020) indicators prior to the COVID-19 lockdown, estimated using a 2SLS model. The dependent variables include ownership of a bank account, ownership of a phone, use of mobile phones for financial transactions, internet usage, and access to money for personal use. Panel A shows results for males, and Panel B for females. The main independent variable is the growth in the value of digital transactions from 2018 to 2019. Standard errors (SE) are reported in brackets, with p-values provided for each estimate. Significance levels are denoted by *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.10$). All regressions include individual and household controls, and the F-statistic from the first stage of the instrumental variable regression is reported. The sample sizes (N) reflect the number of observations used for each regression.

Table A11: Impact of Digital Economy on Employment Structure (2SLS) at extensive margin: Alternative explanatory variable

	(1) All employment	(2) Self-employment	(3) Regular employment	(4) Casual employment
Panel A: Male				
Count (log)	-0.012***	-0.038***	0.036***	-0.006
SE	[0.003]	[0.006]	[0.006]	[0.005]
P-val	[0.001]	[0.000]	[0.000]	[0.273]
N	151696	151696	151696	151696
F-stat from first stage	75.8	75.8	75.8	75.8
Sample Mean	0.739	0.32	0.17	0.212
Panel B: Female				
Count (log)	-0.009	0.001	0.009***	-0.007*
SE	[0.006]	[0.002]	[0.002]	[0.004]
P-val	[0.147]	[0.629]	[0.000]	[0.095]
N	150196	150196	150196	150196
F-stat from first stage	79.69	79.69	79.69	79.69
Sample Mean	0.203	0.045	0.047	0.06

Notes: This table presents the impact of the digital economy on employment structure at the extensive margin, estimated using a 2SLS model with an alternative explanatory variable, the log of the count of digital transactions. The dependent variables include all employment, self-employment, regular employment, and casual employment. Panel A reports results for males, while Panel B reports results for females. The main independent variable is the log of the count of digital transactions, and standard errors (SE) are reported in brackets. P-values indicate the significance of the estimates, with significance levels denoted by *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.10$). All regressions include individual and household controls, and the F-statistics from the first stage are provided to assess the strength of the instrumental variable. Sample means refer to the average proportion of individuals engaged in each employment category. The sample sizes (N) represent the number of observations used in each regression.

Table A12: Impact of growth in amount transacted on employment: 2SLS (ITUS)

	(1) All employment	(2) Self-employment	(3) Regular employment	(4) Casual employment
Panel A: Male				
Growth in amount (2019 over 2018)	-0.078**	-0.244***	0.229***	-0.035
SE	[0.026]	[0.057]	[0.060]	[0.032]
P-value	[0.003]	[0.000]	[0.000]	[0.283]
N	151696	151696	151696	151696
F-stat from first stage	24.3	24.3	24.3	24.3
Sample Mean	0.739	0.32	0.17	0.211
Controls	Yes	Yes	Yes	Yes
Panel B: Female				
Growth in amount (2019 over 2018)	-0.06	0.007	0.058***	-0.044
SE	[0.044]	[0.015]	[0.015]	[0.027]
P-value	[0.167]	[0.631]	[0.000]	[0.111]
N	150196	150196	150196	150196
F-stat from first stage	23.8	23.8	23.8	23.8
Sample Mean	0.203	0.044	0.046	0.06
Controls	Yes	Yes	Yes	Yes

Notes: This table presents the impact of the growth in the amount transacted on various employment outcomes, estimated using a 2SLS model. The dependent variables include all employment, self-employment, regular employment, and casual employment. Panel A reports results for males, while Panel B reports results for females. The main independent variable is the growth in the amount of digital transactions from 2018 to 2019. Standard errors (SE) are reported in brackets, and p-values are provided for each estimate. Significance levels are denoted by *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.10$). All regressions include individual and household controls. The F-statistics from the first stage are reported to assess the strength of the instrumental variable. Sample means represent the average proportion of individuals engaged in each employment category. The sample sizes (N) indicate the number of observations used in each regression.

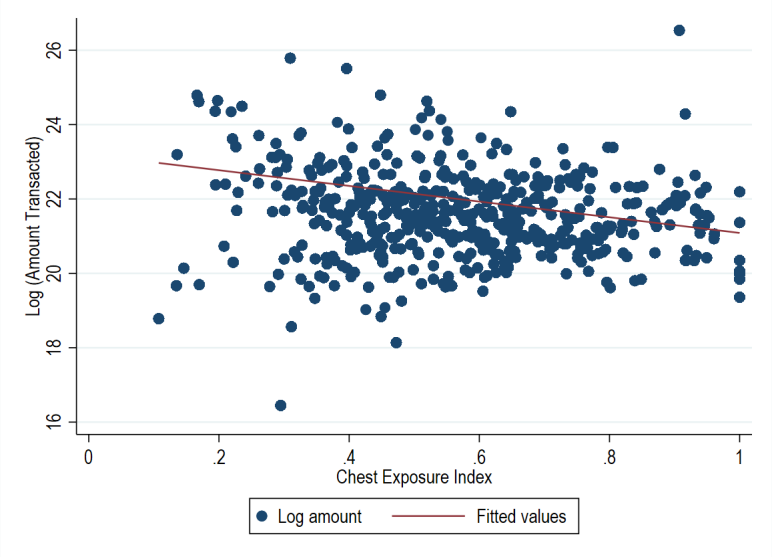


Figure A1: Scatter plot illustrating the relationship between the log of the transaction amount and the Chest Exposure Index, along with a fitted regression line. The scatter plot provides a visual representation of the negative correlation between these two variables, indicating how variations in the log amount reduce with changes in chest exposure.