Digital Payments and Gendered Labor Reallocation

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Abstract

This study examines how digital payments (DP) drive labor reallocation in India, leveraging nationally representative data and a two-stage least squares approach. For men, DP facilitates a shift from agricultural self-employment to formal wage employment. For women, it reduces unpaid labor, promoting entry into formal work and increasing financial autonomy through expanded access to banking, mobile money, and the internet. Both genders experience increased time spent in paid work and earnings. Our findings demonstrate the critical role of DP in transforming labor markets and advancing gender equity.

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1 Introduction

Digital Payments (DP) have revolutionized economic transactions worldwide by lowering transaction costs, broadening financial inclusion, and expanding access to credit, thereby driving economic growth and poverty alleviation across diverse contexts (Jack and Suri, 2014; Suri and Jack, 2016; Demirguc-Kunt et al., 2018; Higgins, 2019; Abiona and Koppensteiner, 2022; Shapiro and Mandelman, 2021; Agarwal et al., 2024; Cong, Giesecke, and Kuhnen, 2024). By 2023, the global digital payments market was valued at approximately \$8.49 trillion, with projections suggesting it will exceed \$15 trillion by 2027. This expansion is driven largely by the rapid adoption of mobile payments, digital banking, and fintech innovations, particularly in developing economies (Statista, 2023; Insights, 2023). These developments have marked DP as a central force in reshaping economic landscapes by integrating previously unbanked populations into formal financial systems and enhancing economic mobility. However, while the macroeconomic benefits of DP are well-documented, further research is required to understand its microeconomic effects on labor markets, time use, and financial autonomy—particularly through a gendered lens.

In 2019, India was ranked 142nd in terms of "Economic Participation and Opportunity" (World Economic Forum, 2023), underscoring substantial gender disparities. Concurrently, the country experienced a dramatic growth in DP (over 285% between 2018 and 2019), further amplified during the COVID-19 pandemic (PhonePe Pulse). This context allows us to examine DP's role in shaping gender-specific labor transitions. Prior research has focused on DP impacts on consumption, economic activity, and labor demand (Agarwal et al., 2024; Crouzet, Gupta, and Mezzanotti, 2023; Dubey and Purnanandam, 2023), yet gaps remain in understanding its influence on gendered labor supply and allocation. This study uniquely addresses these gaps by analyzing DP-driven transitions from informal to formal employment and examining gender-specific time-use shifts within labor and non-labor activities, providing new insights into the gender-differentiated impacts of DP on labor outcomes.

We hypothesize that the proliferation of DP facilitates an economic transformation, with different mechanisms that affect men and women. Increased access to DP is expected to reduce agricultural employment for both genders, a transition supported by structural change theories, which posit that as developing economies modernize, labor shifts from subsistence agriculture to more productive sectors, including non-agricultural self-employment and wage labor (Boppart and Krusell, 2020; Herrendorf, Rogerson, and Valentinyi, 2014;

Lewis et al., 1954). DP, by reducing transaction costs and broadening access, accelerates this transition by enabling more individuals to access formal credit markets and improving labor productivity in non-agricultural sectors (Suri and Jack, 2016).

For women, DP presents transformative opportunities. Structural barriers, including unpaid domestic responsibilities and limited access to financial resources, have historically restricted women's participation in formal labor markets (Duflo, 2012; Dupas and Robinson, 2013; Barth, Kerr, and Olivetti, 2021). DP can reduce gendered barriers to paid and formal employment by fostering financial autonomy, bridging access to credit and markets, alleviating mobility and time constraints, and enabling secure, transparent income management to overcome systemic and cultural inequities. This shift is anticipated to significantly enhance women's participation in the formal economy, helping them transition away from unpaid, unrecognized, and the deep seated disguised form of labor within self-employment.[1]

To substantiate these hypotheses, the study employs 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 insights into labor market participation, time-use patterns, and financial tool utilization, disaggregated by gender, which allows for an exploration of both the demand- and supply-side effects of DP on labor markets.

The empirical strategy incorporates a two-stage least squares (2SLS) methodology to control for potential endogeneity in DP adoption, using district-level exposure to 'currency chest' infrastructure as an instrument, following methodologies outlined by Chodorow-Reich et al. (2020), Crouzet, Gupta, and Mezzanotti (2023), and Das et al. (2023). This approach helps to isolate the exogenous variation in DP access driven by historical banking infrastructure rather than by current economic conditions. Additionally, to ensure compliance with the exclusion restriction, we examine district-level financial and non-financial characteristics that may influence bank chest placements and control for these factors (see Section 5.4.1).

We begin by examining whether DP can catalyze a structural shift from informal, subsistence-oriented activities to formal employment sectors. Subsequently, we analyze the impact of DP at the intensive margin, focusing on changes in time allocated to unpaid versus paid work. Following the labor supply and allocation analysis, we analyze how DP expansion affects key enablers of the digital economy—such as access to banking, internet connectivity, and mobile money—with a specific emphasis on bolstering women's financial autonomy.

[1] 57.3% of India's total workforce is self-employed, with 18.3% working as unpaid labor, category predominantly composed of women (Economic Times, 2024).

For all the above outcomes and their mechanisms, we investigate whether the effects of DP vary by gender.

Our findings at the extensive margins offer insights into how DP influence both the structure of employment and the allocation of labor across genders. For men, we find a significant increase in aggregate employment, driven by reduced agricultural self-employment and increased non-agricultural roles (self-employment and wage/salary employment). For women, the effects differ: aggregate self-employment remains stable, while regular wage/salary employment rises (mainly in the non-agricultural sector), driven by shifts away from unpaid self-employment and casual work. These results suggest that DP facilitates a move from low-productivity agricultural roles to higher-productivity non-agricultural work for men and from unpaid to formal, wage-earning roles for women.

At the intensive margin, DP significantly increase the time men allocate to self-employment and wage/salary employment. For women, DP effects are more pronounced in wage/salary roles, mirroring trends at the extensive margin. Thus, DP not only promote integration into formal labor markets but also increase time in paid work. This rise in employment time, largely drawn from unpaid care and self-care activities, suggests a shift toward more economically productive endeavors. Our analysis also reveals significant wage gains across both self-employed and regularly employed individuals. Crucially, the absence of statistically significant differences in wages between genders suggests that DP promote wage growth in an equitable manner, contributing to narrowing the relative gender wage gaps.

DP also drive socio-economic transformations, notably increasing financial inclusion and autonomy. They boost ownership of bank accounts, mobile phones, and internet usage, engaging more individuals in the digital economy. For women, this access also increased financial autonomy and control over household resources. This shift not only reshapes employment dynamics but also reduces gender disparities in financial access and decision-making.

Disaggregated by gender, age, education and marital status, our results show marked differences in employment engagement. Younger, more educated individuals, particularly those adaptable to digital integration, show increased likelihood of paid employment, underscoring the role of digital literacy in harnessing DP benefits. Unmarried individuals and those from more privileged social categories also exhibit stronger responses to DP, highlighting socio-economic factors as significant mediators of DP effects. In urban settings, DP enhanced regular wage employment for both men and women, demonstrating more effective integration of digital services in urban compared to rural areas. Notably, there is a decrease in self-employment among men from Scheduled Tribes and Scheduled Castes, indicating shifts from traditional livelihoods.

2 Literature Review

Foundational studies by Suri and Jack (2016), Mbiti and Weil (2015), and Jack and Suri (2014) demonstrate how mobile money platforms such as M-Pesa have significantly aided economic growth by providing financial services to unbanked populations, easing credit constraints, and enabling consumption smoothing. These contributions highlight DP's role in poverty alleviation and economic empowerment. Expanding on this, Demirguc-Kunt et al. (2018) and Shapiro and Mandelman (2021) explore DP's potential to mitigate poverty, hunger, and gender inequality and to induce sectoral labor market shifts globally.

Randomized controlled trials (RCTs) offer key insights into the demand-side effects of digital payments (DP) on financial inclusion. Dupas and Robinson (2013) and Field et al. (2021) show that access to savings accounts boosts women's financial autonomy and labor participation in Kenya and India, while Riley (2018) highlights mobile money's role in improving risk-sharing and consumption smoothing in Tanzania, especially for women. De Mel et al. (2022) and Cole, Joshi, and Schoar (2024) also demonstrate improved savings and entrepreneurial outcomes through mobile-linked accounts. However, these studies often have limited geographical scope and overlook time use in paid and unpaid activities. In addition, our study uniquely shows that DP adoption not only enhances financial inclusion but also facilitates broader technology adoption by women, such as mobile and internet use, directly influencing labor reallocation and time use.

Prior research has examined the broader impacts of DP on various economic outcomes. Studies have addressed savings, insurance, liquidity and consumption smoothing (Agarwal et al., 2024; Abiona and Koppensteiner, 2022; De Mel et al., 2022), risk-sharing (Carli and Uras, 2024; Dizon, Gong, and Jones, 2020), 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), intergenerational mobility (Yang et al., 2024; Abiona and Koppensteiner, 2022), 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 is among the first to provide a micro-level analysis of gender-differentiated impacts of DP on labor supply, examining how DP reshape household labor allocation and promote transitions from informal to formal employment. For instance, while Agarwal et al. (2024) focus on the effects of India's 2016 demonetization on accelerating digital payments, our research extends this analysis by exploring how DP facilitate formal employment entry across genders, contributing to the creation of higher-paying job opportunities. We also build on Shapiro and Mandelman (2021)'s findings that firm-level digital adoption reduces self-employment by facilitating transitions into salaried jobs. Notably, this reduction primarily reflects a shift from low-productivity agricultural work to more productive non-agricultural activities, offering a deeper understanding of how DP promote productivity-enhancing labor reallocations. By addressing both the extensive and intensive margins of employment and focusing on intra-household labor dynamics, our analysis provides new insights into how DP drive inclusive economic growth and mitigate gender disparities in labor markets.

3 Data

For our analysis, we use five datasets detailed below.

3.1 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 or unpaid activities. 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 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 gender-disaggregated data on time use patterns in ITUS allow us to study time spent on employment activities by men and women separately. We analyze time spent on all employment activities, regular employment, self-employment and casual employment, alongside unpaid activities, learning and socializing activities and self-care. Our sample is restricted to individuals above age 14. In Table A1, we present a detailed summary statistics of the intensive margin (conditional on positive time spent in the said activity) of time use variables, for both men and women. In Table A2, we present another set of time-use statistics, which we use for additional results and robustness checks.

3.2 Periodic Labor Force Survey (PLFS)

PLFS provides data on the employment and unemployment situation in India. The survey is conducted annually by the National Statistical Office (NSO) since 2017. For our analysis, we used the 2019-20 PLFS wave, 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. We use gender-disaggregated data on the extensive margin of employment activities, including self-employment (disaggregated by agricultural and non-agricultural employment), unpaid self-employment (which is not a part of the aggregate self-employment), regular wage/salary employment, and casual employment. We also use information on individual wages in regular employment and self-employment.[2] To make our analysis consistent with ITUS, we restrict the PLFS sample to individuals over the age of 14. In Table A1, we present the summary statistics of the variables we use from PLFS.

3.3 National Family Health Survey (NFHS)

NFHS is a nationally representative household survey that captures a wide range of topics on health and empowerment. For our analysis, we focus on the fifth round of NFHS, which was conducted in two rounds between 2019 and 2021. From the Pre COVID-19 round, we draw the following individual-level information 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. The data for women is drawn from the eligible women dataset of NFHS, where the sample is restricted to women between the age group of 15-49. 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 UPI usage data from Phonepe

We extract 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', an

[2] It is worth noting that the data for overall wages/earnings from employment are not available in PLFS.

online repository of digital transaction data from Phonepe users, available for each quarter from the year 2018. Our district-level treatment variable is the average of the total amount of digital transactions over the years 2018 and 2019. To add additional layers of robustness, we use the total count of DP averaged over the same period and the growth of DP between 2018 and 2019 as an alternative treatment variable. We observe wide variations in UPI usage, as shown in Table A2. Furthermore, in Figure A1, we observe a rapid growth in UPI usage between 2018 and 2019.

3.5 RBI data on Currency Chests

A few scheduled banks have been granted permission by the Reserve Bank to set up currency chests 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. We obtain district-level data on the number of currency chests in 2016, curated by Crouzet, Gupta, and Mezzanotti (2023), which was originally obtained from RBI. This data is available for 512 districts, excluding districts from northeastern states and union territories. For the purpose of our analysis, we merged these district-level data with ITUS, PLFS, and NFHS separately.

4 Identification Strategy

To analyze the impact of DP 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. To mitigate these concerns, we employ an IV approach. We instrument district-level DP using the currency chest exposure index, $Chest_d$, for each district. This choice is inspired by Chodorow-Reich et al. (2020) and Crouzet, Gupta, and Mezzanotti (2023), followed by Aggarwal, Kulkarni, and Ritadhi (2023) and Das et al. (2023), who leveraged historical variations in currency chest as a quasi-random instrument in the context of demonization in 2016.[3] The chest exposure index, $Chest_d$, derived from Crouzet et al. (2024), measures the proportion of total deposits in a district held by banks operating currency

[3]As of November 2016, there were approximately 4,000 chests distributed throughout the country, receiving newly printed notes either directly from one of the 19 Reserve Bank of India (RBI) issue offices or via around 600 hub chests (Chodorow-Reich et al., 2020).

chests. This index reflects the significance of these banks in each district, derived from detailed deposit and branch data. The relationship is given by:

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

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, and D_{jbd} represents the deposits in bank b of type j in district d. Chest_d captures variations in cash availability across districts, with higher scores indicating easier access to cash, reducing reliance on digital transactions.

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; Cramer et al., 2024). 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 Panel (a) of Figure 1. 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 -0.30.

The overlapping histogram in Panel (b) of Figure 1 highlights the distinct distributions of the chest exposure index (blue) and the normalized amount of DP (orange). The chest exposure index is concentrated at lower values, representing limited regional access to the infrastructure, while the broader distribution of DP reflects significant variation across regions. This separation reinforces the validity of using chest exposure as an IV. The concentrated distribution of chest exposure indicates its exogeneity, as regional access to currency chests is unlikely to correlate with unobserved factors directly influencing transaction volumes. Meanwhile, the broader, dispersed distribution of digital transactions points to multiple underlying determinants, suggesting that chest exposure affects transaction volumes indirectly through its role in expanding access to financial infrastructure. The lack of overlap between the distributions supports the exclusion restriction.

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). Complementarities in the adoption of DP play a key role in the validity of our instrument. Complementarities arise when the benefits of adopting DP increase with the number of users. These dynamics further justify using district-level exposure to currency chest infrastructure as an IV, capturing spatially quasi-random variations in the promotion, of DP.

To further demonstrate that chest exposure in 2016 can serve as an instrument for DP in 2018-19, we reference the work of Dubey and Purnanandam (2023). Their study utilizes the district-level exogeneity based on early and late adoption of UPI by lead banks, and reveals that the higher impact for early adopters persisted well beyond the launch of UPI in 2016. This finding aligns with the evidence of strong network externalities in the adoption of DP, as shown by Crouzet, Gupta, and Mezzanotti (2023) and Higgins (2019).

The first stage regression estimates the relationship between the chest exposure index and the amount of DP (log), controlling for individual and district-level characteristics. The second stage regression is:

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

where Y_{ids} is the outcome variable of interest for individual i residing in district d, state s. D_ds is the predicted treatment variable from the first stage. X is a vector of individual-specific control variables and Z is another vector of district-specific control variables. α_s is state specific dummy variables. In this stage, the main coefficient of interest (β) captures the causal impact of DP on the outcome variables. We cluster our standard errors at the district level. To ensure the robustness of our results, we conduct an alternative specifications test by using the growth and count of DP as the treatment variable.

5 Empirical Analysis

We begin by analyzing the gender-disaggregated effects of digital payments on the likelihood of employment by occupation and gender (extensive margin). Subsequently, we examine the impacts on time spent in each type of employment (intensive margin). As outlined in Section 4, the primary results are estimated using the IV-2SLS approach. However, the baseline OLS estimates align with the 2SLS findings, underscoring their robustness. Table A3 presents the OLS estimates for the extensive margin, focusing on employment type dummies derived from the PLFS dataset. Similarly, Table A4 provides the OLS estimates for the intensive margin for paid employment activities. The subsequent subsections delve into the discussion of the main 2SLS estimates.

5.1 Extensive Margin: DP and Likelihood of Employment

Our findings on *aggregate employment*,[4] presented in Figure 2, and in Table A5, indicate that a 1% increase in district-level DP leads to a 1.2 percentage point (pp) increase in *aggregate employment* for men, while the corresponding effect for women is a 0.6 pp increase, though not statistically significant. Notably, the difference in these estimates is not statistically significant (see Table A5), suggesting that while the effect for women is smaller, it nonetheless trends in a positive direction.

Estimates on the impact of DP on employment structures reveal gender-specific transitions. For men, a 1% increase in district-level DP leads to a significant decline in *self-employment* (by 2.7 pp), *casual employment* (by 0.9 pp), and *unpaid self-employment* (1.2 pp), while a corresponding increase of 4.8 pp is observed for *regular wage employment*. This indicates a stronger movement from self-employment to more formal wage-based roles.

In contrast, for women, the effect of DP is characterized by a significant shift from *unpaid self-employment* and *casual employment* to *regular wage employment*, while there is no change in *self-employment (paid)*. *Unpaid self-employment* declined more strongly for women (by 2.3 pp), *casual employment* decreased (by 1.0 pp), while regular wage employment rose (by 1.7 pp). Unlike men, women's transition is from unpaid and casual-insecure work to more stable wage employment, underscoring a different pathway toward formalization in the labor market. These findings suggest that DP promotes formal employment for both genders but through distinct transitions—self-employment to regular employment for men, and unpaid to regular employment for women.

To examine the underlying mechanism of this shift towards formal employment, we decompose employment into its sectoral components. More specifically, we focus on employment in agricultural and non-agricultural sectors. The estimated coefficients using 2SLS are presented in Figure 3 (and Table A6). The rise in *aggregate employment* for men (Figure 2), is driven by a decline in *agricultural employment* (by 6.3 pp) with a more than proportionate rise in *non-agricultural employment* (by 7.5 pp). A similar pattern is observed in

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

self-employment, where the decline in *agricultural self-employment* (by 5.2 pp) is bigger than the gains in non-*agricultural self-employment* (by 2.5 pp), leading to a decline in aggregate *self-employment* (by 2.7 pp, Figure 2). This is a case of structural change, where a shift from subsistence agriculture to a more productive sector is observed.

For women, we observe a shift towards non-agricultural sector, albeit to a lesser extent as compared to men. We see a reduction in *agricultural employment* (by 1.4 pp) and an increase in *non-agricultural employment* (by 2.0 pp). Although the increase in the latter is higher, it is not large enough, as reflected in the statistically insignificant increase in *aggregate employment* (Figure 2). Additionally, the muted impacts on *agricultural self-employment* (decrease by 0.5 pp) and *non-agricultural self-employment* (increase by 0.5 pp) is consistent with null impact on aggregate *self-employment* (Figure 2).

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

In this section, we examine the intensive margins of employment (time spent in paid and unpaid activities, conditional on being employed) using the ITUS, 2019.

The results presented in Panel (a) of Figure 4 (Table A7) show that men, who are in *any employment*, spent 6.7 minutes more on paid activities with 1% increase in DP (1.63% rise over the sample mean). The gains for men in self-employment is 8.7 minutes (2.2% over the sample mean).[5] Additionally, there is a 4.5 minute gain in *regular-wage employment*, which is a 1% increase relative to the sample mean. The overall increase in employment time, as shown in Panel (a) of Figure 4, is accompanied by reductions in time-spent on *unpaid activities* (caregiving and home production) by 3.8 minutes, *self-care* (sleeping and related activities) by 5.8 minutes (Panel (b)), and *casual employment* by 4.2 minutes, though the latter is not statistically significant.

For women, the intensive margin results, on aggregate, are largely similar to those for men (z-score for statistical difference is insignificant (Table A7)). However, the point estimates for *any employment* and *self-employment*, while positive, are not statistically significant. With regards to *regular wage employment*, we observe a significant increase of 7.8 minutes (not statistically different to men); however, this represents a 2.1% rise over the sample mean, which is notably higher than the 1% increase observed for men.

[5]At the extensive margin, we observe a decline in *self-employment* (Figure 2), suggesting that some men are moving out of *self-employment*. However, at the intensive margin, those who remain self-employed are spending more time on *self-employment* activities, indicating deeper labor market engagement.

As shown in Panel (b) of Figure 4, the increase in time spent on paid activities for women, like men, is driven by a reduction in *unpaid activities* (by 7.1 minutes), equivalent to a 3.1% decrease over the sample mean, and in *self-care* (by 5.8 minutes), representing a 0.9% reduction over the sample mean. However, unlike men, for whom no significant effect on time spent in *learning, socializing, and cultural activities* was found, women exhibit a significant increase in this category (by 8.9 minutes), a 5.5% rise over the sample mean. This shift for women could be linked to greater use of digital technologies, such as mobile phones and the internet, as discussed in the next section. These findings suggest a potential reallocation of women's time to self-development activities, which may support skill acquisition and long-term employment opportunities.

Building on the analysis of time allocation in employment, which demonstrates an equitable increase across genders, we examined the impact of DP on total annual earnings from *self-employment* and *regular wage employment*.[6] As shown in Table A8, while the absolute gains in earnings are higher for men (INR 1,120 for self-employment and INR 1,074 for regular employment) compared to women (INR 693 and INR 1,125), the percentage increased are more pronounced for women (13% and 16%) than for men (10% and 13%). However, insignificant z-scores for statistical differences across genders, indicate equitable growth in earnings which is commensurate with the increase in time spent on paid activities.

5.3 DP and Enablers of Digital Economy

So far, we have studied the impacts of DP on the supply-side shifts in employment patterns. However, for a more holistic understanding of the impacts of DP, we explore how the proliferation of DP affects the demand for enables of digital economy: access to banks, mobile phones and the internet. Additionally, we analyze the changes in digital transactions at an individual level, and the overall impact on women's financial autonomy.

Using the NFHS data, in Figure 5 (Table A9), we show that a 1% increase in DP led to a 3 pp and 2.1 pp increase in *ownership of bank accounts* for men and women, respectively (statistically indifferent across genders). *Mobile phone ownership* increased for women by 7.4 pp, which is significantly higher than the increase for men (by 1.1 pp). This underscores the higher increase in *learning, social and cultural activities* found in Panel (b) of Figure 4. We observe a 8.2 pp increase in the *use of internet* for women, compared to the 6.9 pp increase for men, however, the difference across gender is statistically insignificant. Additionally, in

[6] Sourced from PLFS, which does not provide earnings data for aggregate or casual employment.

terms of usage of DP, we observe a 2.8 pp increase in *use of mobile for financial transactions* for women, compared to 3.9 pp increase for men, again there is no statistical difference in the observed effects across genders. Lastly, we examined the impact of DP on financial autonomy (*money that you can yourself use*) to gauge control over financial resources. This variable is only available for women and the results show a significant increase of 4.9 pp.

In summary, the expansion of DP not only restructured employment patterns but also significantly enhanced access to digital enablers, particularly for women. We find substantial increases in mobile phone ownership, internet usage, and financial autonomy for women, complementing their rise in self-development activities. These shifts underscore the role of DP in promoting equitable access to digital resources and greater financial independence, with broader implications for gender equity in the labor market.

5.4 Heterogeneity and Robustness

We conduct heterogeneity analyses to explore how DP impacts employment across various socioeconomic groups, accounting for factors like age, education, marital status, caste, and place of residence.

In Figure A2, we find that transitions to regular employment driven by DP are evident for men in both rural and urban sectors. For women, however, these effects are predominantly observed in urban settings, aligning with broader access to digital infrastructure in cities. In Figure A3, marginalized caste groups exhibit more pronounced shifts towards regular employment across both genders, indicating a more equitable distribution of DP benefits among socially disadvantaged groups.

Further analysis, considering age, education, and marital status (Figures A4, A5, A6), reveals that young and middle-aged and less-educated individuals primarily drive these transitions. This is because DP reduces financial barriers, increases accessibility, and promotes economic mobility, particularly for those more adaptable to labor market shifts. Among married individuals, we observe shifts from self-employment to regular employment for men, while for women, movements from casual employment to regular wage employment are more frequent. These findings suggest that DP particularly supports economically vulnerable and marginalized groups, promoting inclusive participation in the labor market.

Additionally, time allocation between goods and services shows gender-specific trends (Table A10). Self-employed men are increasingly shifting toward service-oriented work, reflecting a sectoral reallocation towards services. For women in regular wage employment, we observe an increased engagement in service-related activities with minimal shifts in goods production. These patterns, corroborated by reductions in unpaid labor (Table A11), highlight the potential of DP to drive structural shifts in labor markets, particularly benefiting women and self-employed men.

5.4.1 Robustness of IV

To further ensure the exogeneity of our IV, we control for any district-level variable that could affect the exposure to chest banks, such as (i) share of villages with ATM in the district, (ii) share of villages with bank branch in the district, (iii) population density, (iv) number of illiterate persons, (v) distance to state capital, (vi) credit society to population ratio and (vii) employment rate. In Table A12, we regress these district-specific variables onto our chest exposure index, and find that share of villages with ATM and population density are correlated significantly with chest exposure. Therefore, as a robustness check, we control for these two factors in our main results, presented in Table A13. Our results do not change even after including these district-specific controls.

5.4.2 Other Robustness Checks

Furthermore, we carry out the following test to check the robustness of our estimates. First, we use the average log count of digital transactions between 2018 and 2019 as an alternative treatment variable, instead of average log amount. The results are produced in Table A14 for extensive margin of employment and in Table A15 for intensive margin of employment, again for four types of employment categories. We find that the results are consistent with our main results.

Secondly, 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 A16 and intensive margin results in Table A17, which are again found to be consistent with our original set of results.

6 Conclusion

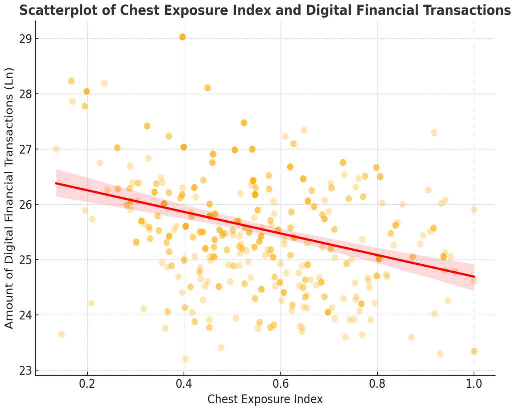
This study examines the causal effects of Digital Payments (DP) on labor market dynamics in India, emphasizing differential impacts across genders. Our analysis reveals that DP catalyzes significant shifts in employment structures, particularly transitioning labor towards more productive sectors. For men, this transition is characterized by a pronounced reduction in agricultural self-employment coupled with increased participation in non-agricultural sectors. For women, the movement away from unpaid self-employment to regular wage employment marks a crucial step towards access to formal labor markets and dismantling of traditional gender roles.

On the intensive margin, DP markedly increases labor time across both self and regular wage employment, yielding significant wage gains for both genders. Importantly, these gains are comparable for women, thereby contributing to narrowing the gender wage gap and enhancing gender equality in labor market outcomes. Moreover, the reallocation of time from unpaid domestic and caregiving activities to productive employment highlights a shift in household labor dynamics that is particularly beneficial for women, reinforcing the role of DP in promoting gender equity.

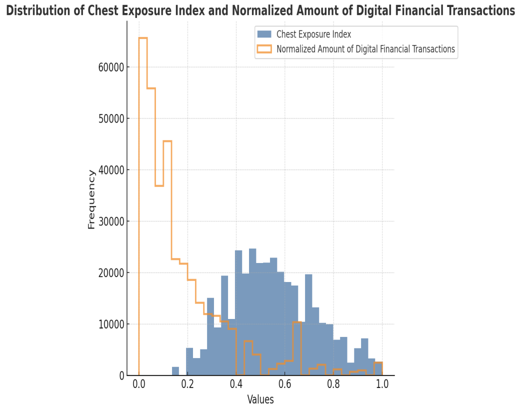
Furthermore, DP bolsters financial autonomy for both men and women by enhancing access to banking services and enabling mobile-based financial transactions. For men, this access facilitates income diversification, particularly into more productive non-agricultural sectors, fostering broader economic growth. For women, increased access to financial tools—banks, mobile phones, the internet, and DP—empowers them to engage more actively in wage-based employment and formal financial systems, thereby expanding their economic agency. For women in particular, the adoption of formal financial instruments promotes greater financial independence and supports more equitable economic participation.

In summary, this paper illustrates that DP serves as a potent catalyst for structural changes in the labor market, effectively reshaping traditional gender roles and reducing disparities in labor and financial inclusion. The profound potential of DP to foster labor market participation and drive substantive social change underscores its capacity to promote gender equity and economic empowerment for women. The enduring impacts of these dynamics suggest that the widespread adoption of DP is pivotal for achieving gender-equitable and sustainable labor market outcomes.

7 Figures



(a) Scatterplot of Chest Exposure and Amount of DP (Log)



(b) Distribution of Chest Exposure and Normalized DP

Figure 1: **Panel (a): Correlation between the *Chest Exposure Index* and the *Amount of Digital Financial Transactions* (log-transformed), trimmed at 1%.** The scatterplot presents individual data points along with a fitted trend line and 95% confidence intervals (shaded). The negative slope indicates a moderate negative correlation with a coefficient of -0.30, suggesting that higher chest exposure is associated with lower digital financial transaction volumes. **Panel (b): Distribution of the *Chest Exposure Index* (blue) and the *Normalized Amount of Digital Financial Transactions* (orange).** The normalized transaction amounts are scaled between 0 and 1 for comparability. Both variables are displayed using 30 bins, and the distinct shapes of the distributions indicate that the Chest Exposure Index is concentrated at lower values, while the digital financial transactions are more widely spread.

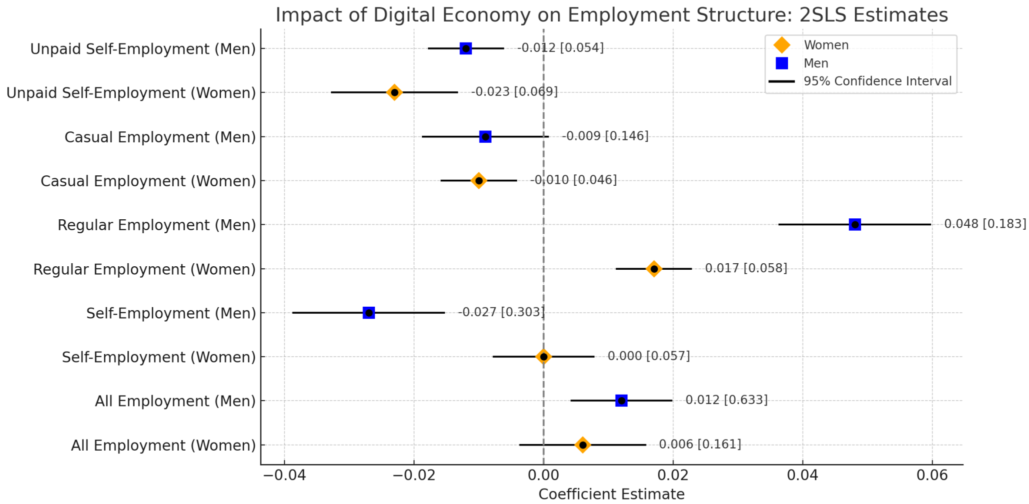


Figure 2: Impact of DP on Employment Structure: 2SLS Estimates. *Notes:* The figure presents 2SLS estimates of the impact of DP on various employment categories, differentiated by gender. Coefficient estimates and 95% confidence intervals are shown. The coefficient values are reported next to each variable, and the sample means are reported in parentheses. Square markers represent estimates for men, while diamond markers represent estimates for women. The vertical dashed line at zero indicates the reference point for no effect. The dependent variable in each model is a dummy variable. For all employment, 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 labor force. 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. Y-axis shows the outcome variables of employment in aggregate employment, self-employment, regular wage employment, causal employment and unpaid self-employment. The X-axis represents the local average treatment effects in percentage points. Data: PLFS, 2019-2020, RBI Chest Exposure, 2016 and Phone Pay data (2018, 2019).

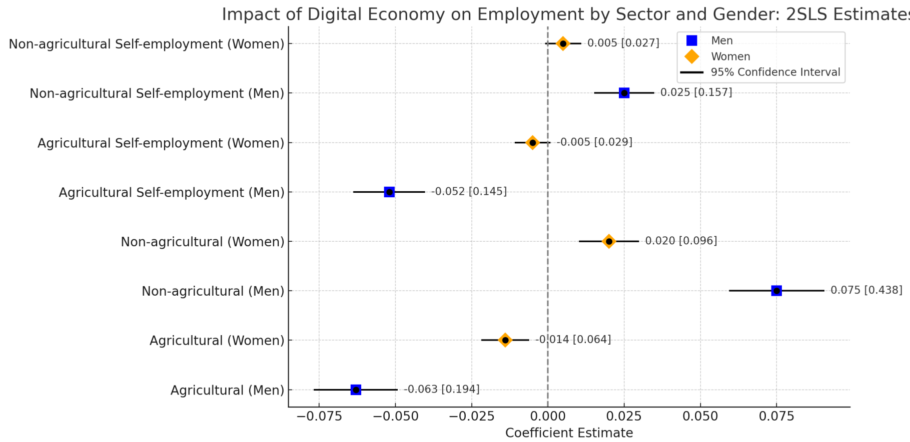


Figure 3: **Impact of DP on Employment and Self-Employment by Sector: 2SLS Estimates**. *Notes:* This figure presents 2SLS estimates analyzing the impact of DP on employment in the agricultural and non-agricultural sectors. The coefficient estimates and 95% confidence intervals are displayed. The coefficient values are reported next to each variable, and the sample means are reported in parentheses. Squares represent estimates for men, and diamonds represent estimates for women. The vertical dashed line indicates the reference point for no effect. Agricultural self-employment is a dummy variable that captures activities related to farming and allied sectors, while non-agricultural self-employment covers informal businesses and entrepreneurial activities. Y-axis shows the outcome variables. The X-axis represents the local average treatment effects in percentage points. Data: PLFS, 2019-2020, RBI Chest Exposure, 2016 and Phone Pay data (2018, 2019).

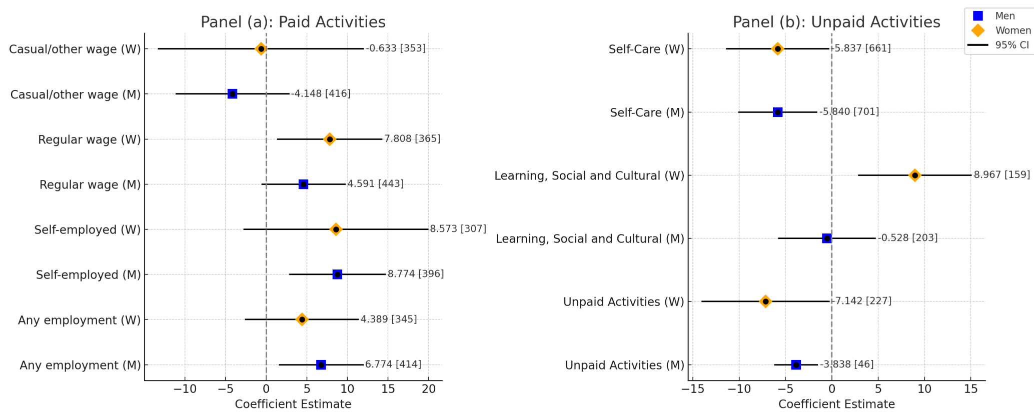


Figure 4: **Impact of DP on Time Spent on Paid and Unpaid Activities (minutes per day)**: 2SLS Estimates. *Notes:* The figure presents 2SLS estimates of the impact of DP on time allocation to paid and unpaid activities. Square markers represent men's estimates, and diamond markers represent women's estimates. Coefficient estimates and 95% confidence intervals are displayed. The coefficient values are reported next to each variable, and the sample means are reported in parentheses. The vertical dashed line indicates no effect. Y-axis shows variables for paid (Panel (a)) and unpaid (Panel (b)) activities, for Men (M) and Women (W). Analysis for paid activities is conducted separately for those employed in any category, self-employed, and regular wage employed. The analysis on unpaid activities (including unpaid domestic services, learning, social, and cultural activities, and self-care) is reported only for employed persons. The X-axis represents the local average treatment effects in minutes per day. Data: ITUS, 2019, RBI Chest Exposure, 2016 and Phone Pay data (2018, 2019).

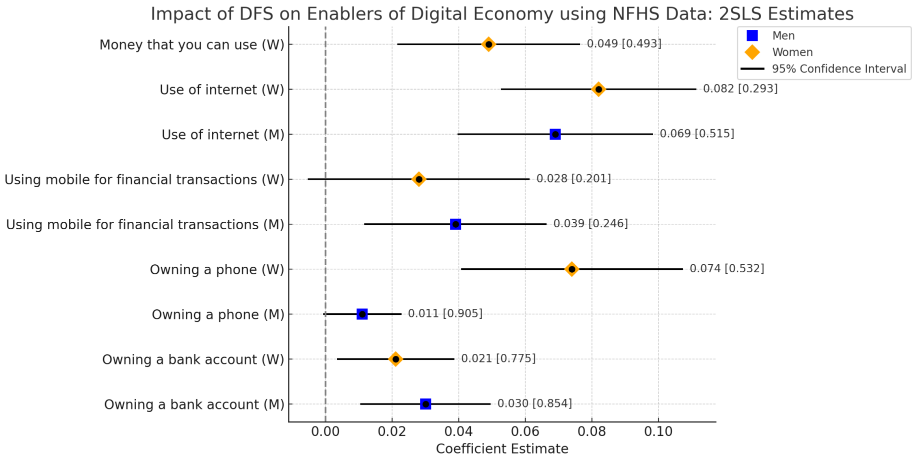


Figure 5: **Impact of DP on Enablers of Digital Economy: 2SLS Estimates.** *Notes:* This figure shows 2SLS estimates for the impact of digital transactions on enablers of digital economy. The indicators include owning a bank account, owning a phone, using a mobile for financial transactions, using the internet, and access to money for personal use. Coefficient estimates and 95% confidence intervals are presented. The coefficient values are reported next to each variable, and the sample means are reported in parentheses. Squares represent estimates for men, while diamonds represent estimates for women. The vertical dashed line at zero indicates no effect. Y-axis shows the outcomes variables. All these dependant variables are in the form of dummy variables where 'yes; is coded as '1' and 'no' as '0'. The X-axis represents the local average treatment effects in percentage points. Data: NFHS (2019), RBI Chest Exposure (2016) and Phone Pay data (2018, 2019).

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Online Appendix

Table A1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
	Men			Women			Difference in Mean	
	N	Mean	SD	N	Mean	SD		
A. PLFS 2019-2020	Extensive Margin							
All Employment	127,677	0.633	0.482	125,580	0.162	0.368	0.47	***
- Employed in Agriculture	127,677	0.195	0.396	125,580	0.065	0.246	0.130	***
- Employed in Non-agriculture	127,677	0.439	0.496	125,580	0.097	0.295	0.342	***
Self Employed	127,677	0.303	0.459	125,580	0.057	0.232	0.246	***
- Employed in Agriculture	127,677	0.145	0.352	125,580	0.029	0.169	0.116	***
- Employed in Non-agriculture	127,677	0.158	0.364	125,580	0.029	0.164	0.130	***
Unpaid Self Employed	127,677	0.054	0.227	125,580	0.069	0.253	-0.015	***
Regular Employed	127,677	0.184	0.387	125,580	0.058	0.001	0.126	***
Casual Employed	127,677	0.146	0.353	125,580	0.046	0.209	0.100	***
	Intensive Margin							
Wages for self-employment activities	38,714	10888.1	10043.1	7,186	4844.3	5838.9	6043.8	***
Wages for Regular salary/wage activities	42,204	8980.5	14534.6	13,119	6997.2	13058.5	1983.4	***
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	82,444	45.90	71.97	16,535	227.33	130.99	-181.43	***
Learning, Social & Cultural	82,444	202.57	112.11	16,535	159.39	97.29	43.19	***
Self-Care	82,444	700.81	87.21	16,535	660.70	82.47	40.10	***
C. NFHS Data 2019								
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 Men and Women, comparing various employment measures across agricultural and non-agricultural sectors. Columns (1)-(3) report statistics for Men, while columns (4)-(6) correspond to Women. Column (7) highlights the difference in means between Men and Women, 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, regular employment, casual 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 (C) incorporates indicators defining enablers of digital economy from the National Family Health Survey (NFHS). Differences between Men and Women are statistically tested, with significance levels marked as * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

Table A2: Additional Summary Statistics

Panel A: Additional summary statistics from TUS data								
	Men			Women			Difference in Mean	
	N	Mean	SD	N	Mean	SD		
	Intensive Margin (Minutes Spent)							
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 DP 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
Chest Exposure Index	512	0.569	0.189	0.107	0.44	0.70	1
Growth in amount of transactions	512	1.107	0.29	-0.90	0.98	1.22	2.53
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
Density	510	452.2	357.6	2	205	607	2913
Distance to state capital	512	0.216	0.134	0	0.118	0.293	0.787
Credit Societies per 1000 persons	512	0.043	0.089	0	0.007	0.041	1.178
Worker population Ratio	512	0.409	0.068	0.258	0.352	0.463	0.572
Illiterate Persons (log)	512	13.35	0.772	9.18	12.90	13.91	14.93

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 district-level characteristics. Differences in means between Men and Women 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 A3: Extensive Margin for Types of Employment Dummies, OLS Model (PLFS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All employment	Agricultural Employment	Non-agricultural Employment	Self-employment	Agricultural Self-employment	Non-agricultural Self-employment	Unpaid Self-employment	Regular employment	Casual Employment
					Panel A: Men				
Amount(log)	0.009***	-0.049***	0.057***	-0.027***	-0.040***	0.013***	-0.012***	0.047***	-0.012***
SE	[0.002]	[0.004]	[0.004]	[0.003]	[0.003]	[0.002]	[0.001]	[0.004]	[0.003]
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
N	127677	127677	127677	127677	127677	127677	127677	127677	127677
Sample Mean	0.633	0.194	0.438	0.303	0.145	0.157	0.054	0.183	0.146
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
					Panel B: Women				
Amount(log)	0.004	-0.015***	0.019***	-0.006***	-0.008***	0.003***	-0.018***	0.017***	-0.007***
SE	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.002]
P-value	[0.172]	[0.000]	[0.000]	[0.002]	[0.000]	[0.010]	[0.000]	[0.000]	[0.000]
N	125580	125580	125580	125580	125580	125580	125580	125580	125580
Sample Mean	0.161	0.064	0.096	0.057	0.029	0.027	0.069	0.058	0.046
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 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 A4: Impact of digital transactions on time spent on paid activities: Intensive Margin (OLS Model)

	(1)	(2)	(3)	(4)
	All employment	Self-employment	Regular employment	Casual employment
Panel A: Men				
Amount (log)	8.585***	9.599***	4.957***	2.727
SE	[1.478]	[1.647]	[1.278]	[1.732]
P-value	[0.000]	[0.000]	[0.000]	[0.116]
N	82444	35763	21087	25594
R-Square	0.052	0.049	0.071	0.059
Sample Mean	414	396	443	416
Controls	Yes	Yes	Yes	Yes
Panel B: Women				
Amount (log)	6.148***	7.266*	11.282***	-1.749
SE	[1.698]	[3.220]	[1.667]	[2.560]
P-value	[0.000]	[0.024]	[0.000]	[0.495]
N	16535	4465	5353	6717
R-Square	0.031	0.034	0.091	0.043
Sample Mean	344	307	365	353
Controls	Yes	Yes	Yes	Yes

Notes: 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 Men, and Panel B for Women. 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 A5: Impact of Digital Economy on Employment Structure (2SLS) using PLFS data: Extensive Margin

	Type of employment dummy (2SLS)				
	(1)	(2)	(3)	(4)	(5)
	All Employment	Self-Employment	Regular Employment	Casual Employment	Unpaid Self-Employment
	Panel A: Men				
Amount (log)	0.012***	-0.027***	0.048***	-0.009*	-0.012***
SE	[0.004]	[0.006]	[0.006]	[0.005]	[0.003]
P-val	[0.001]	[0.000]	[0.000]	[0.065]	[0.000]
N	127677	127677	127677	127677	127677
F-stat from first stage	61.74	61.74	61.74	61.74	61.74
Sample Mean	0.633	0.303	0.183	0.146	0.054
	Panel B: Women				
Amount (log)	0.006	0.000	0.017***	-0.010***	-0.023***
SE	[0.005]	[0.004]	[0.003]	[0.003]	[0.005]
P-val	[0.235]	[0.992]	[0.000]	[0.001]	[0.000]
N	125580	125580	125580	125580	125580
F-stat from first stage	65.907	65.907	65.907	65.907	65.907
Sample Mean	0.161	0.057	0.058	0.046	0.069
Z-Score	0.937	3.744***	4.621***	0.171	1.886**

Notes: (i) These models estimate the impact of digital transactions on the incidence of employment by gender. (ii) The dependent 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 labor 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 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 A6: Impact of Digital Economy on Employment by Sector using PLFS Data: Extensive Margin

	(1)	(2)	(3)	(4)
	All Employment		Self-Employment	
	Agricultural	Non-agricultural	Agricultural	Non-agricultural
	Panel A: Men			
Amount (log)	-0.063***	0.075***	-0.052***	0.025***
SE	[0.007]	[0.008]	[0.006]	[0.005]
P-val	[0.000]	[0.000]	[0.000]	[0.000]
N	127677	127677	127677	127677
F-stat from first stage	61.74	61.74	61.74	61.74
Sample Mean	0.194	0.438	0.145	0.157
	Panel B: Women			
Amount (log)	-0.014***	0.020***	-0.005	0.005
SE	[0.004]	[0.005]	[0.003]	[0.003]
P-val	[0.001]	[0.000]	[0.153]	[0.114]
N	125580	125580	125580	125580
F-stat from first stage	65.907	65.907	65.907	65.907
Sample Mean	0.064	0.096	0.029	0.027
Z-score	6.078***	5.830***	7.006***	3.430***

Note: This table shows the impact of the digital economy on employment outcomes in agricultural and non-agricultural sectors, also with a focus on self-employment. Columns (1) and (2) report the effects on agricultural and non-agricultural employment, while columns (3) and (4) analyze self-employment, differentiating between agricultural and non-agricultural activities. Agricultural self-employment is a dummy variable that captures activities related to farming and allied sectors, while non-agricultural self-employment covers informal businesses and entrepreneurial activities. 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. 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 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 A7: Impact of digital transactions on time spent on paid and unpaid activities: Intensive Margin

	2SLS and Control Variables						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Any employment	Self-employed	Regular wage	Casual Employment	Unpaid Activities	Learning, Social and Cultural	Self-Care
	Panel A: Men						
Amount (log)	6.774**	8.774***	4.591*	-4.148	-3.838***	-0.528	-5.840***
SE	[2.661]	[3.038]	[2.650]	[3.573]	[1.202]	[2.696]	[2.182]
P-value	[0.011]	[0.004]	[0.083]	[0.246]	[0.001]	[0.845]	[0.007]
N	82444	35763	21087	25594	82444	82444	82444
F-stat from first stage	73.767	82.859	37.22	100.487	73.767	73.767	73.767
Sample Mean	414	396	443	416	46	203	701
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: Women						
Amount (log)	4.389	8.573	7.808**	-0.633	-7.142**	8.967***	-5.837**
SE	[3.580]	[5.811]	[3.312]	[6.477]	[3.531]	[3.135]	[2.844]
P-value	[0.220]	[0.140]	[0.018]	[0.922]	[0.043]	[0.004]	[0.040]
N	16535	4465	5353	6717	16535	16535	16535
F-stat from first stage	58.549	74.528	40.382	45.426	58.549	58.549	58.549
Sample Mean	345	307	365	353	227	159	661
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Z-Score	0.535	0.031	0.758	0.475	0.886	2.296**	0.000

Notes: (i) These models estimate the impact of digital transactions on time spent on paid (columns 1-3) and unpaid (columns 4-6) activities by gender. (ii) Analysis for paid activities is conducted separately for those employed in any category, self-employed, and regular wage employed. The analysis in columns (4-6) on unpaid activities (including unpaid domestic services, learning, social, and cultural activities, and self-care) is reported only for employed persons. (iii) The main explanatory variable is the district-level amount transacted via digital platform (PhonePe), averaged over 2018 and 2019. (iv) All models are estimated using 2SLS where the main explanatory variable is instrumented with district-level exposure to bank chests. (v) Control variables are included in all models. (vi) Robust standard errors are clustered at the district level (in parentheses). (vii) Asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A8: Impact on Wages (2SLS) using PLFS: Intensive Margin

	(1)	(2)	(3)	(4)
	Earnings from self-employment Activity		Earnings from Regular Wage Activity	
	Men	Women	Men	Women
Amount (log)	1120.380***	693.508**	1074.966***	1125.994***
SE	[245.749]	[288.406]	[271.260]	[369.764]
P-val	[0.000]	[0.016]	[0.000]	[0.002]
N	38714	7186	42204	13119
F-stat from first stage	65.483	30.526	54.3	42.106
Sample Mean	10888	4844	8981	6997
Z-Score	1.127		0.111	

Notes: (i) These models estimate the impact of digital transactions on the average wage. (ii) The dependent variable in models (1 & 2) and (3 & 4) is gross earning for last 30 days from self-employment activity; and from 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 is the district-level amount transacted via digital platform (PhonePe), averaged over 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. (vii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A9: Impact of DP on Enablers of Digital Economy using NFHS Data: 2SLS Estimation

	(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: Men					
Amount (log)	0.030***	0.011*	0.039***	0.069***	
SE	[0.010]	[0.006]	[0.014]	[0.015]	
P-val	[0.002]	[0.077]	[0.005]	[0.000]	
N	45626	45626	41296	45626	
F-stat from first stage	31.375	31.375	29.794	31.375	
Sample Mean	0.854	0.905	0.246	0.515	
Panel B: Women					
Amount (log)	0.021**	0.074***	0.028*	0.082***	0.049***
SE	[0.009]	[0.017]	[0.017]	[0.015]	[0.014]
P-val	[0.023]	[0.000]	[0.094]	[0.000]	[0.000]
N	53117	53117	28284	53117	53117
F-stat from first stage	32.766	32.766	20.385	32.766	32.766
Sample Mean	0.775	0.532	0.201	0.293	0.493
Z-Score	0.669	3.495***	0.499	0.613	

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 is the district-level amount transacted via digital platform (PhonePe), averaged over 2018 and 2019. (iv) All models are estimated using 2SLS model and include control variables. (v) 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. (viii) Data source: NFHS and Phonepay.

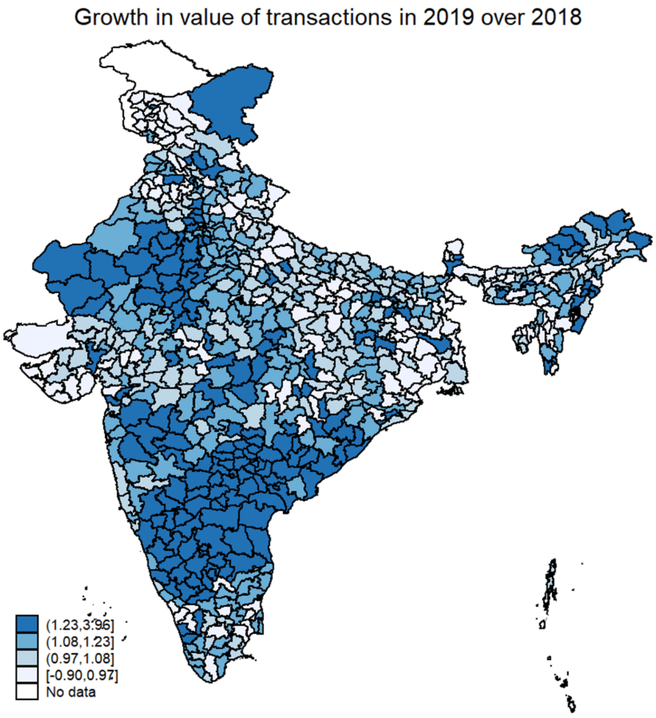

Figure A1: District-level maps of DP growth.

Notes: We show the growth rates of amount of digital transactions between 2018 and 2019. Here, -0.90 to 0.97 represents growth of DP between -90% and 97%. Regions covered in darker shades mean higher growth in DP. Growth rate for the darkest shade is between 123% and 396%. Data: Phone Pay Pulse, UPI 2018 and 2019.

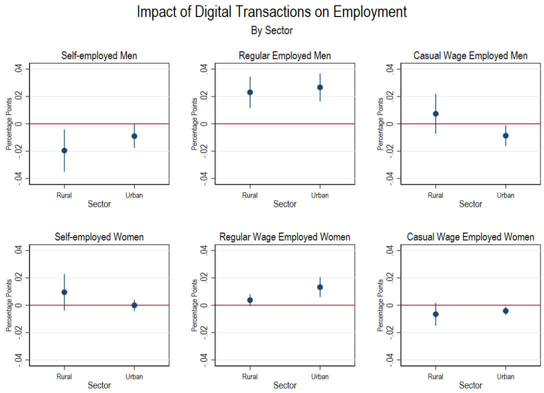

Figure A2: Impact of DP on Employment (Extensive Margin) by Sector

Notes: This figure presents the effect of DP 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. All models are estimated using the 2SLS method, where the main explanatory variable is the district-level amount transacted via the digital platform (PhonePe), averaged over 2018 and 2019. Each panel corresponds to a specific employment category: self-employed, casual employment, and regular wage employment for both men and women.

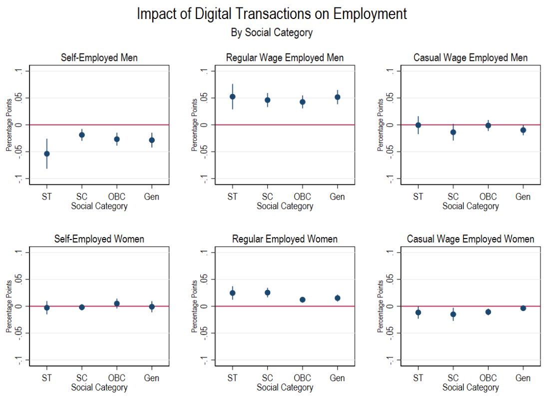

Figure A3: Impact of DP on Employment (Extensive Margin) by Caste Groups

Notes: This figure presents the effect of DP on employment outcomes, disaggregated by gender and caste (SC/ST/OBC/General), across various employment categories. The y-axis represents the percentage point change in employment outcomes, and the x-axis shows the caste (SC/ST/OBC/General). The blue points indicate the estimated coefficients, while the vertical lines represent 95% confidence intervals. All models are estimated using the 2SLS method, where the main explanatory variable is the district-level amount transacted via the digital platform (PhonePe), averaged over 2018 and 2019. Each panel corresponds to a specific employment category: self-employed, casual employment, and regular wage employment for both men and women.

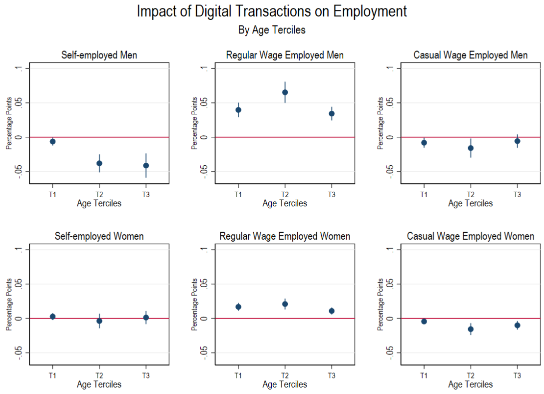

Figure A4: Impact of DP on Employment (Extensive Margin) by Age terciles

Notes: This figure presents the effect of DP on employment outcomes, disaggregated by gender and age terciles, across various employment categories. The y-axis represents the percentage point change in employment outcomes, and the x-axis shows the age terciles. The blue points indicate the estimated coefficients, while the vertical lines represent 95% confidence intervals. All models are estimated using the 2SLS method, where the main explanatory variable is the district-level amount transacted via the digital platform (PhonePe), averaged over 2018 and 2019. Each panel corresponds to a specific employment category: self-employed, casual employment, and regular wage employment for both men and women. In this figure, we see that the impact of DP on employment is stronger for young people, especially young women.

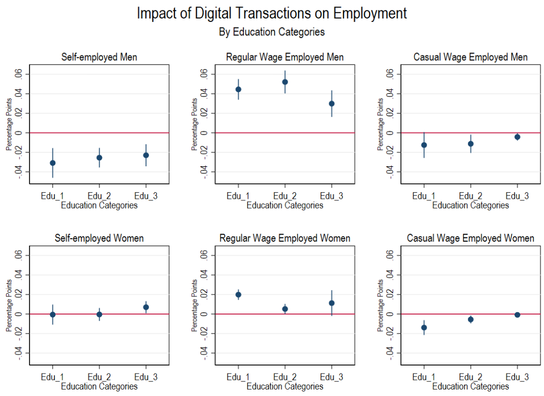

Figure A5: Impact of DP on Employment by Education Categories

Notes: This figure presents the effect of DP on employment outcomes, disaggregated by gender and education categories, across various employment categories. Edu_1 represents persons with up to primary education, Edu_2 are those with middle, secondary, higher secondary or Diploma, Edu_3 is for graduates and above. The y-axis represents the percentage point change in employment outcomes, and the x-axis shows the education categories. The blue points indicate the estimated coefficients, while the vertical lines represent 95% confidence intervals. All models are estimated using the 2SLS method, where the main explanatory variable is the district-level amount transacted via the digital platform (PhonePe), averaged over 2018 and 2019. Each panel corresponds to a specific employment category: self-employed, casual employment, and regular wage employment for both men and women.

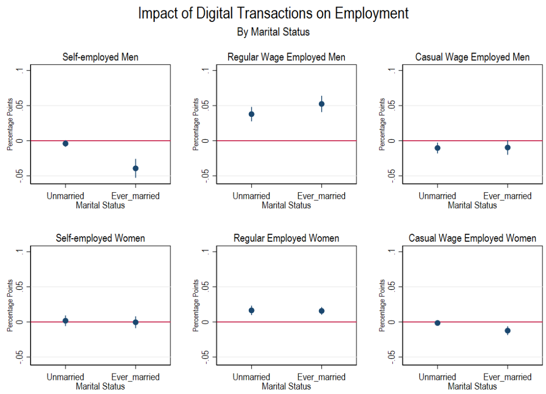

Figure A6: Impact of DP on Employment by Marital Status

Notes: This figure presents the effect of digital transactions on employment outcomes, disaggregated by gender and marital status, across various employment categories. The y-axis represents the percentage point change in employment outcomes, and the x-axis shows the marital status (unmarried/ever-married). The blue points indicate the estimated coefficients, while the vertical lines represent 95% confidence intervals. All models are estimated using the 2SLS method, where the main explanatory variable is the district-level amount transacted via the digital platform (PhonePe), averaged over 2018 and 2019. Each panel corresponds to a specific employment category: self-employed, casual employment, and regular wage employment for both men and women.

Table A10: Division of time spent on production of goods and services: 2SLS Model

	(1)	(2)	(3)	(4)
	Any employment	Self Employed	Regular Wage	Casual Wage
Panel A: Men				
	Dependent Variable: Time spent on production of goods			
Amount (log)	-17.769***	-18.463***	5.492	-12.371*
SE	[4.664]	[5.115]	[4.682]	[6.559]
P-value	[0.000]	[0.000]	[0.241]	[0.059]
N	82444	35763	21087	25594
F-stat from first stage	73.767	82.859	37.22	100.487
Sample Mean	184	188	66	276
Controls	Yes	Yes	Yes	Yes
	Dependent Variable: Time spent on production of services			
Amount (log)	13.302**	21.113***	9.569	5.619
SE	[4.915]	[6.022]	[9.754]	[5.163]
P-value	[0.007]	[0.000]	[0.327]	[0.277]
N	82444	35763	21087	25594
F-stat from first stage	73.767	82.859	37.22	100.487
Sample Mean	132	167	128	87
Controls	Yes	Yes	Yes	Yes
Panel B: Women				
	Dependent Variable: Time spent on production of goods			
Amount (log)	-12.132**	1.119	9.992*	-7.729
SE	[5.929]	[6.728]	[5.170]	[9.832]
P-value	[0.041]	[0.868]	[0.053]	[0.432]
N	16535	4465	5353	6717
F-stat from first stage	58.549	74.528	40.382	45.426
Sample Mean	170	180	42	266
Controls	Yes	Yes	Yes	Yes
	Dependent Variable: Time spent on production of services			
Amount (log)	20.267***	8.67	20.047**	14.817**
SE	[5.026]	[6.227]	[8.905]	[5.953]
P-value	[0.000]	[0.164]	[0.024]	[0.013]
N	16535	4465	5353	6717
F-stat from first stage	58.549	74.528	40.382	45.426
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 A11: Impact of digital transactions on time spent on other (unpaid) activities (2SLS): By Employment Category

	(1)	(2)	(3)
	Unpaid Activities	Learning, Social and Cultural	Self-Care
Panel A1: Self-employed men			
Amount(log)	-5.000**	-0.671	-6.767***
SE	[1.935]	[3.212]	[2.300]
P-value	[0.010]	[0.834]	[0.003]
N	35763	35763	35763
F-stat from first stage	82.859	82.859	82.859
Sample Mean	53	217	708
Panel A2: Regular wage-employed men			
Amount(log)	-1.829	-2.03	-2.847
SE	[1.158]	[3.067]	[2.724]
P-value	[0.114]	[0.508]	[0.296]
N	21087	21087	21087
F-stat from first stage	37.22	37.22	37.22
Sample Mean	35	190	675
Panel B1: Self-employed women			
Amount(log)	-4.244	9.287**	-11.120***
SE	[4.378]	[4.718]	[3.417]
P-value	[0.332]	[0.049]	[0.001]
N	4465	4465	4465
F-stat from first stage	74.528	74.528	74.528
Sample Mean	264	177	670
Panel B2: Regular wage-employed women			
Amount(log)	-11.553***	3.192	1.053
SE	[3.551]	[3.454]	[3.143]
P-value	[0.001]	[0.355]	[0.738]
N	5353	5353	5353
F-stat from first stage	40.382	40.382	40.382
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 A12: Chest Exposure and District-specific variables

Dependent Variable: Exposure to Chest Banks			
	Coefficient	SE	P-val
Share of villages with ATM	0.615**	0.209	0.003
Share of villages with Bank Branch	0.045	0.117	0.699
Population Density	-0.0001***	0.00003	0.004
Illiterate Persons (log)	-0.014	0.012	0.240
Distance to State capital	0. 061	.0632	0.337
Credit society to population ratio	-0.100	0.092	0.279
Employment Rate	-0.103	0.153	0.498
N	510		

Notes: This table presents estimates from an OLS regression of the district-specific characteristics on the chest exposure index. Share of villages with ATM is the ratio of number of villages with at least one ATM to the total number of villages in the district. Share of villages with bank branch is the ratio of number of villages with at least one bank branch to the total number of villages in the district. Density of the population density in the district. Illiterate persons (log) is the logarithm of total number of illiterate persons in the district. Distance to state capital is the total kilometre distance between the district and the state capital. Credit society to population ratio is the number of credit societies per 1000s. Employment rate is the ratio of working population to total population. Data for these district-level variables are taken from Crouzet, Gupta, and Mezzanotti (2023). Significance levels are denoted by *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.10$).

Table A13: Impact of Digital Economy on Employment Structure (2SLS) using PLFS Data and Additional District-level Controls: Extensive Margin

	Type of employment dummy (2SLS)			
	(1)	(2)	(3)	(4)
	All Employment	Self-Employment	Regular Employment	Casual Employment
Panel A: Men				
Amount (log)	0.012**	-0.021***	0.043***	-0.011*
SE	[0.005]	[0.007]	[0.008]	[0.007]
P-val	[0.013]	[0.004]	[0.000]	[0.096]
N	127532	127532	127532	127532
F-stat from first stage	45.898	45.898	45.898	45.898
Sample Mean	0.633	0.303	0.184	0.146
Panel B: Women				
Amount (log)	0.009	0.002	0.014***	-0.007*
SE	[0.007]	[0.006]	[0.004]	[0.004]
P-val	[0.189]	[0.770]	[0.000]	[0.074]
N	125418	125418	125418	125418
F-stat from first stage	47.825	47.825	47.825	47.825
Sample Mean	0.161	0.057	0.058	0.046
Z-score	0.349	2.495**	3.242***	0.496

Notes: (i) These models estimate the impact of digital transactions on the incidence of employment by gender, with additional district-specific controls (Share of villages with ATMS, share of villages with bank branches, population density and education category) (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. Data for district-level controls are taken from the dataset curated by Crouzet, Gupta, and Mezzanotti (2023). Standard deviations (SD) are reported in parentheses, and differences between Men and Women are statistically tested, with significance levels marked as * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

Table A14: Impact of Digital Economy on Employment Structure (2SLS) at extensive margin (PLFS): Alternative explanatory variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All employment	Agricultural Employment	Non-agricultural Employment	Self-employment	Agricultural Self-employment	Non-agricultural Self-employment	Unpaid Self-employment	Regular employment	Casual Employment
					Panel A: Men				
Count (log)	0.012***	-0.064***	0.076***	-0.027***	-0.052***	0.025***	-0.012***	0.049***	-0.009*
SE	[0.004]	[0.007]	[0.009]	[0.006]	[0.006]	[0.005]	[0.003]	[0.006]	[0.005]
P-val	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.065]
N	127677	127677	127677	127677	127677	127677	127677	127677	127677
F-stat from First Stage	56.745	56.745	56.745	56.745	56.745	56.745	56.745	56.745	56.745
Sample Mean	0.633	0.194	0.438	0.303	0.145	0.157	0.054	0.183	0.146
					Panel B: Women				
Count (log)	0.006	-0.014***	0.020***	0	-0.005	0.005	-0.024***	0.017***	-0.010***
SE	[0.005]	[0.004]	[0.005]	[0.004]	[0.003]	[0.003]	[0.005]	[0.003]	[0.003]
P-val	[0.234]	[0.001]	[0.000]	[0.992]	[0.153]	[0.111]	[0.000]	[0.000]	[0.001]
N	125580	125580	125580	125580	125580	125580	125580	125580	125580
F-stat from First Stage	60.472	60.472	60.472	60.472	60.472	60.472	60.472	60.472	60.472
Sample Mean	0.161	0.064	0.096	0.057	0.029	0.027	0.069	0.058	0.046

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 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 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 A15: Impact of digital transactions on time spent on paid activities in intensive margin: Alternate explanatory variable

Explanatory variable: Count of digital transactions				
	(1)	(2)	(3)	(4)
	Any employment	Self Employed	Regular Wage	Casual Wage
	Panel A: Men			
Count (log)	6.736**	8.732***	4.618*	-4.072
SE	[2.659]	[3.024]	[2.684]	[3.498]
P-value	[0.011]	[0.004]	[0.085]	[0.244]
N	82444	35763	21087	25594
F-stat from first stage	69.451	78.817	33.016	102.426
Sample Mean	414	396	443	416
Controls	Yes	Yes	Yes	Yes
	Panel B: Women			
Count (log)	4.322	8.427	7.876**	-0.61
SE	[3.518]	[5.710]	[3.324]	[6.251]
P-value	[0.219]	[0.140]	[0.018]	[0.922]
N	16535	4465	5353	6717
F-stat from first stage	55.804	73.642	35.884	46.973
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 Men. (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 A16: Impact of Growth in Digital Economy on Employment Structure (2SLS) at extensive margin (PLFS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All employment	Agricultural Employment	Non-agricultural Employment	Self-employment	Agricultural Self-employment	Non-agricultural Self-employment	Unpaid Self-employment	Regular employment	Casual Employment
					Panel A: Men				
Growth in Amount	0.055***	-0.297***	0.352***	-0.127***	-0.242***	0.115***	-0.057***	0.226***	-0.044*
SE	[0.018]	[0.053]	[0.063]	[0.035]	[0.045]	[0.026]	[0.016]	[0.043]	[0.024]
P-val	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.067]
N	127677	127677	127677	127677	127677	127677	127677	127677	127677
F-stat from First Stage	33.095	33.095	33.095	33.095	33.095	33.095	33.095	33.095	33.095
Sample Mean	0.633	0.194	0.438	0.303	0.145	0.157	0.054	0.183	0.146
					Panel B: Women				
Growth in Amount	0.03	-0.067***	0.098***	0	-0.022	0.022	-0.112***	0.079***	-0.049***
SE	[0.026]	[0.023]	[0.026]	[0.021]	[0.016]	[0.015]	[0.031]	[0.018]	[0.017]
P-val	[0.238]	[0.004]	[0.000]	[0.992]	[0.164]	[0.134]	[0.000]	[0.000]	[0.004]
N	125580	125580	125580	125580	125580	125580	125580	125580	125580
F-stat from First Stage	33.388	33.388	33.388	33.388	33.388	33.388	33.388	33.388	33.388
Sample Mean	0.161	0.064	0.096	0.057	0.029	0.027	0.069	0.058	0.046

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 is growth in amount from 2018 to 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 A17: Impact of growth in amount transacted on time spent on productive activities: 2SLS

Dependent variable: Time spent on productive activities				
	(1)	(2)	(3)	(4)
	Any employment	Self employed	Regular wage	Casual Wage
Panel A: Men				
Growth in amount (2019 over 2018)	42.336**	56.550**	24.568	-28.18
SE	[19.376]	[22.062]	[15.617]	[24.162]
P-value	[0.029]	[0.010]	[0.116]	[0.243]
N	82444	35763	21087	25594
F-stat from first stage	23.887	23.065	24.639	18.234
Sample Mean	414	396	443	416
Controls	Yes	Yes	Yes	Yes
Panel B: Women				
Growth in amount (2019 over 2018)	30.15	61.764	39.836**	-6.104
SE	[24.934]	[44.504]	[17.154]	[62.607]
P-value	[0.227]	[0.165]	[0.020]	[0.922]
N	16535	4465	5353	6717
F-stat from first stage	26.628	24.247	32.458	13.944
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 Men (Panel A) and Women (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.

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