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ABSTRACT

Improving First-Generation College Students' Education and Employment Outcomes: Effects of a Targeted Scholarship Program*

We evaluate the First-Generation Graduate Scholarship scheme implemented in the Indian state of Tamil Nadu, which waives tuition fees for first-generation college students in technical education. Using household survey data in difference-in-differences (DiD) and synthetic DiD frameworks, we find substantial improvements in enrollment, stream choice, and graduation in technical courses, with downstream effects on regular employment, occupational choices, and household welfare. Male students gained more than female students. The scheme also increased reliance on education loans to cover residual costs. Our findings highlight how targeting intergenerational disadvantages through education policy can influence educational choices and produce positive labour market returns.

JEL Classification: I23, I24, I28, J24

Keywords: first-generation graduates, technical courses, tuition fee waiver, higher education, stream choice, labour market outcomes

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1 Introduction

Countries with greater income inequality tend to exhibit stronger intergenerational persistence of economic advantage and disadvantage; in such societies, wealth and social status are often transmitted across generations, hindering social mobility and perpetuating inequality (Corak, 2013; Kundu and Sen, 2023). In poorer countries, children born to uneducated parents are less likely to have the means to pursue education themselves (Van Der Weide et al., 2024). Since parents with higher levels of human capital have greater resources to invest in their children's education, and the returns on investment are larger at the higher education level (Psacharopoulos and Patrinos, 2018), this dynamic can further reinforce cycles of disadvantage. Without public policy interventions that enhance human capital in ways that disproportionately benefit the disadvantaged, these trends are likely to persist (Solon, 2004).

Over the past few decades, affirmative action policies in developing countries have made notable progress in improving access to primary education for children from disadvantaged backgrounds (Iversen et al., 2017). However, these gains have not translated meaningfully into higher education access or significant income mobility. College education increasingly serves as a gateway to higher earnings (Montenegro and Patrinos, 2014), yet many developing countries rarely implement affirmative action policies specifically targeting higher education. In several of these countries, even secondary education remains either unsubsidized or only partially subsidized, restricting access to a small, privileged segment of the population (Duflo et al., 2023). The failure to provide adequate training to talented young individuals solely due to their families' economic disadvantages represents a socially inefficient allocation of resources.

Against this backdrop, this study evaluates the impact of a tuition fee waiver scheme for higher education in India that uses first-generation college student (FGCS) status as its sole eligibility criterion. FGCS refers to individuals who are the first in their families to attend college. Targeting such students is particularly important, given that parental education and employment significantly influence children's educational and labour market outcomes (Chetty et al., 2024; Duflo et al., 2024; Stansbury and Schultz, 2023). In India, although intergenerational educational persistence has declined at the lower end of the fathers' educational distribution, persistence has increased at the top (Azam and Bhatt, 2015).

The scheme, known as the first-generation graduate scholarship (FGGS) scheme, has been implemented in Tamil Nadu since 2010. It aims to waive the entire "tuition fees" for first-generation college students taking technical education courses such as Engineering, Medicine, and Agriculture at the undergraduate level. The sole criterion for eligibility is that the student should be the first one in the family to go to college, irrespective of gender, caste, religion, and income status of the family. The FGGS scheme is one of the most extensive affirmative action programs on higher education in Tamil Nadu, and around 10% to 16% of the total budget for the state's higher education is spent on this program every year since its inception.[1] As of January 2021, a cumulative total of 2.21 million students (2,213,556) have benefited from tuition fee concessions totalling Rs 4,408 crores (approximately USD 624 million, at an exchange rate of 1 USD = Rs 70.64) under this scheme (Government of Tamil Nadu, 2021).

We examine the program's effects on technical course enrollment and stream choice among first-generation college students in this context. We use repeated cross-sectional household survey data from the National Sample Survey (NSS) to estimate the impact on enrollment. Further, we also explore the labour market consequences of the program on the target group. The pooled data for this analysis are sourced from NSS rounds and the Periodic Labour Force Survey (PLFS).

We use difference-in-differences (DiD) and synthetic difference-in-differences (synthetic DiD) frameworks to assess the intent-to-treat (ITT) effects of the program, relying on the exogenous timing of its implementation for identification. We select the neighbouring states of Kerala and Karnataka as the control group in the DiD model, considering their socio-economic and cultural similarities with the treatment state, Tamil Nadu. Synthetic DiD method involves constructing a synthetic control state for Tamil Nadu as a weighted combination of 18 large Indian states (which are comparable to the treatment state) selected to closely mirror Tamil Nadu's pre-intervention characteristics. We compare the trends in technical enrollment and stream choice of first-generation college-goers in the age cohort of 17–22 years in the treated state with that of the first-generation college-goers in the same cohort from the control states. We consider the years 2004, 2007, and 2009 to be the pre-intervention period and the years 2011, 2014, and 2017 to be the post-intervention period in the pooled data. We also conduct robustness tests, including event study, placebo analysis and subsample analysis with border districts.

In the event study framework, formal tests for joint significance of pre-treatment coefficients reveal no statistically significant differences, supporting the assumption of parallel trends between treatment and control groups prior to the implementation of the FGGS scheme. Our findings suggest that the FGGS scheme increased technical course enrollment by 3.7 percentage points and increased the likelihood of choosing a technical course instead of a non-technical course by eight percentage points among first-generation individuals. The synthetic DiD analysis further confirms these findings, reporting a treat-

[1] Calculated by author from the state government budget expenditure notes (See budget notes for year 2014-15: https://tnbudget.tn.gov.in/tnweb_files/budgethighlights/2014-15/Highlights_2014-2015_English.pdf (accessed in April 2025)).

ment effect of 4.2 percentage points for technical course enrollment and 8.5 percentage points for stream choice. The robustness of our findings is further reinforced by consistent results across various approaches, including event study analyses, placebo tests, and subsample analyses using samples from the bordering districts.

We also conduct heterogeneity analysis examining variations in the treatment effect across gender, religion, caste, rural-urban residence, and household's educational background. This approach acknowledges that intergenerational educational mobility in India is influenced by intersecting social identities, with socio-economic disparities persisting among marginalized groups such as Scheduled Castes (SC), Scheduled Tribes (ST), women, and those living in rural areas. We observe differential impacts of the program across demographic groups. In particular, there are notable gender differences, with male students benefiting more from the program than female students.

Focusing on individuals for the analysis of labour market outcomes, we find that the scheme had a positive and significant impact in terms of increasing the likelihood of having a technical graduate degree among the beneficiaries. This implies that the scheme was not only successful in enrolling students in technical degree courses but also in improving the completion rates among the targeted group. Beyond educational attainment, the FGGS scheme has demonstrable impacts on labour market outcomes. Beneficiaries of the program are more likely to secure regular salaried employment and less likely to engage in casual labour, indicating a shift towards more stable and formal job opportunities. Furthermore, the scheme facilitates transitions from agricultural employment to the service sector, reflecting a move towards higher-skilled industries. Notably, there is an increased likelihood of beneficiaries occupying associate professional roles, suggesting upward occupational mobility enabled by the program.

We explore suggestive mechanisms through which the FGGS scheme impacts educational and labour market outcomes. Our analysis reveals that the scheme facilitates access to technical courses by complementing tuition fee waivers with increased reliance on education loans, primarily from institutional lenders, to meet residual costs. We also observe that the scheme effectively reduced the proportion of household expenditure allocated to education. Furthermore, the FGGS scheme significantly enhances social welfare, as evidenced by a notable rise in monthly per capita expenditure among recipients.

Our analysis offers the first empirical evaluation of a large-scale affirmative action policy explicitly targeted at first-generation college students. The FGGS scheme stands as one of the most ambitious and expensive higher education initiatives in Tamil Nadu, yet its effectiveness has remained unexamined in the empirical literature. While the state government publicly releases annual aggregated beneficiary statistics, a critical challenge lies in the absence of pre-implementation data on first-generation student status, and data on non-applicants. Moreover, no nationally representative surveys conducted in India have information on first-generation status of the individual. Our study addresses these data limitations by estimating the program's intention-to-treat effect using household survey data. Given the constraints, this approach offers the most feasible and policy-relevant identification strategy.

Our analysis directly engages with the growing literature on first-generation college students. This literature highlights a qualitative distinction between individuals from families with no history of post-secondary education and those with such a background. First-generation college students, who often come from socioeconomically disadvantaged backgrounds (Adamecz-Völgyi et al., 2020; Henderson et al., 2020), face a range of structural and behavioural barriers throughout their educational and labour market trajectories. Compared to peers with college-educated parents, FGCS are significantly less likely to access and complete higher education (Adamecz-Völgyi et al., 2020; Toutkoushian et al., 2021). They frequently underestimate their abilities, make suboptimal academic and career choices (Shure and Zierow, 2023), anticipate lower non-wage returns even in high-paying occupations (Adler et al., 2025), and continue to face disadvantages in the labour market (Stansbury and Rodriguez, 2024). However, none of these existing studies explicitly examine a targeted policy that identifies FGCS as a specific type of socio-economic disadvantage and implements an affirmative action policy based on this criterion.

We also engage with and extend the literature on identity-based affirmative action in higher education. One of the important discourses on affirmative action programs is about selecting the intended beneficiaries of the programs. Critics argue that identity-based affirmative action programs often disproportionately benefit economically privileged individuals within disadvantaged identity groups, potentially reallocating opportunities from less advantaged members of privileged identity groups to relatively advantaged individuals within marginalized groups (Bertrand et al., 2010). In response to such concerns, scholars have proposed alternative targeting mechanisms that go beyond identity or income-based criteria. For instance, Basant and Sen (2014) advocates using parental education as a more accurate indicator of educational disadvantage. The FGGS scheme in Tamil Nadu follows this logic, using the educational attainment of household members as the sole eligibility criterion. This framework enables us to empirically examine a non-identity-based affirmative action policy. Importantly, it allows us to explore whether such a policy produces more equitable outcomes. Our findings reveal differential impacts across demographic groups: relatively privileged groups, such as males and urban residents, benefit more from the program. This suggests that even when eligibility is based on educational disadvantage rather than identity, program effects may still vary systematically along social lines, raising important questions about how non-identity-based policies can be designed to better serve marginalized populations.

At the same time, this study contributes to policy debates on designing efficient policies without compromising equity (Muralidharan, 2024). Most importantly, our findings speak to ongoing debates in India, where traditional caste-based reservations are increasingly contested on the grounds of inefficiency, and where there is growing demand for class-based alternatives. The FGGS program offers a compelling model that targets students in need without compromising representation.

We also contribute to the extant academic discourse concerning interventions aimed at promoting higher education. Tertiary education plays a transformative role in shaping individuals' employment, earnings, and job security outcomes (Sánchez and Singh, 2018), with evidence pointing to exceptionally high private returns compared to other education levels (Montenegro and Patrinos, 2014). Higher education is also widely recognized as a key driver of national economic growth (Castelló-Climent and Mukhopadhyay, 2013; Bloom et al., 2006). Our study adds evidence to this discourse by assessing the effects of FGGS scheme on labour market outcomes and social welfare.

Finally, this study contributes to the growing literature on intergenerational mobility (Duflo et al., 2024; Asher et al., 2024; Chetty et al., 2014). The FGGS scheme marks a significant step toward bridging the gap between families with differing levels of educational attainment. In a developing country like India, a university degree not only signals academic achievement but also confers social status and economic capital. Educational attainment often perpetuates a cycle of socio-economic privilege, with advantages being transmitted across generations. As a result, disparities in parental education can entrench long-term inequality (Lillard and Willis, 1994). By targeting first-generation students, the FGGS program directly intervenes in this cycle, offering a pathway for upward mobility.

The rest of the paper is organized as follows. In Section 2, we describe details about the program. Section 3 describes the dataset's main variables and presents some descriptive analysis. Section 4 explains the empirical model. The results of the analysis are discussed in Section 5. Section 6 concludes the paper.

2 Background: FGGS scheme

First-generation college students are the target beneficiaries of the first-generation graduate scholarship scheme, which defines eligibility based on the absence of any household member with a prior college degree.[2] Introduced in Tamil Nadu in the academic year

[2] The concept of first-generation college students (or first-generation graduates, or first-in-family attending college) emerged initially within administrative frameworks to delineate eligibility for federal

2010–11, the FGGS scheme is the first in India to recognize first-generation college students as a distinct disadvantaged group and to design a scholarship program specifically targeting their needs. The scheme waives tuition fees for first-generation college students pursuing technical education courses such as Engineering, Medicine, and Agriculture. The sole criterion for selecting students is that the student should be the first graduate of the family, with no regard to the gender, religion, caste and income status of the family for eligibility.

FGCS can avail the scholarship once secured admission from any of the government, government-aided and private institutions in the state through the government's single-window counselling system.[3] To avail the scheme, students have to obtain the "No Graduate" certificate issued by the competent revenue authority, and the same should be submitted at the time of counselling.[4]

The state government also fixes tuition fee rates for government colleges, while a committee appointed by the government determines the fees for private self-financing institutions. For example, in 2019–20, tuition fees for engineering colleges were set between Rs 2,000 and Rs 27,500, depending on the institution type (Government of Tamil Nadu, 2019). Colleges where FGCS are admitted are required to provide tuition fee concessions in accordance with these norms and collect only the balance amount from students. The total tuition fees waived under the FGGS scheme are subsequently reimbursed to the colleges by the state government. The data shows that 1,91,268 students were benefited with Rs. 402.69 crore (approximately USD 58 million) spent on this program in the academic year 2018-19 alone. The percentage of beneficiaries, calculated as the ratio of the number of students who benefited to the total undergraduate enrollment, varies over the years from 8.45% in 2018-19 to 14.81% in 2013-14 (Table A.2).

initiatives in the USA (Ives and Castillo-Montoya, 2020).While the prevailing definition typically focuses on parental educational background (Dennis et al., 2005; Pike and Kuh, 2005; Ishitani, 2006), existing literature also advocates for a broader criterion that encompasses not only parental education but also that of siblings (York-Anderson and Bowman, 1991).

[3] The single window admissions system is a centralised admission process utilised by several prominent universities in Tamil Nadu. Specifically, Anna University employs it for engineering admissions, MGR University for medical admissions, and Tamil Nadu Agricultural University for agriculture courses. Upon application, students are ranked based on their scores (12th standard exam scores, with the National Eligibility cum Entrance Test (NEET) score being adopted for medical courses since 2017-18), and they are then invited to participate in an Admissions Counseling Process according to their rank.

[4] The student must obtain a certificate from the Headquarters Deputy Tahsildar of their place of residence, confirming that no member of their household has completed a college degree.

3 Data

3.1 Data description

To assess the impact of the FGGS scheme on technical enrollment, we use repeated cross-sectional data at the household level from multiple rounds of the National Sample Survey (NSS), corresponding to 2004, 2007, 2009, 2011, 2014, and 2017.[5] Though these surveys focus on various topics, they all contain common information relevant for our analysis, including socio-economic characteristics of households, demographic and educational details of each household member, and the current enrollment status of family members aged 5–29 years. The FGGS scheme was introduced in 2010, making the period covered by these surveys suitable for a comparative analysis of pre- and post-implementation outcomes.

Our main empirical analysis defines Tamil Nadu as the treated state while using the neighbouring states of Karnataka and Kerala as the control group to evaluate the program in a difference-in-differences framework. Additionally, we conduct a synthetic DiD analysis that uses data from all the large states of India to create the counterfactual group; this analysis is explained in detail in Section 4.3.

As explained below, the sample for our main analysis on education outcomes considers individuals who are in the target group of the FGGS scheme, i.e., those in the college-going age group of 17-22 years. Additionally, to assess the impact of the FGGS scheme on subsequent labour market outcomes, we focus on the period when eligible candidates are expected to enter the labour market. Given that technical courses typically take 4 to 5.5 years to complete, we define the age group of 25–29 years as the potential age for labour market entry.

Eligible candidates started entering the labour market in mid-2014. For our analysis, we use three rounds of survey data from the years 2007, 2009, and 2011, collected prior

[5] Specifically, we use the following rounds of NSS data: 61st round survey on "Employment and Unemployment" collected in 2004-05, 64th round survey on "Participation and Expenditure in Education" collected in 2007-08, 66th round survey on "Employment and Unemployment" collected in 2009-10, 68th round survey on "Employment and Unemployment" collected in 2011-12, 71st round survey on "Social Consumption: Education" collected in 2014, and 75th round survey on "Household Social Consumption: Education" collected in 2017-18. Thus, we create pooled cross-sectional data sourced from six years of surveys.

to this period[6], and two rounds of survey data from 2017 and 2018[7], collected after this period, which provides information on individuals' employment status. Therefore, the repeated cross-sectional household-level data for the labour market analysis are drawn from the 2007, 2009, 2011, 2017, and 2018 rounds of the National Sample Survey (NSS).[8]

Additionally, to examine the complementary role of education loans as a suggestive mechanism, we use the 70th round of the NSS survey for the year 2013 on debt and investment, which includes detailed information on loans borrowed at the household level. Below, we explain the construction of the sample and key variables for education and labour market outcomes.

3.2 Main variables on education outcomes

Since the policy is aimed at undergraduate students, we define the age of 17-22 as the relevant age group for our analysis, as individuals from this age group are likely to be enrolled in undergraduate studies (Figure A.1). Individuals are eligible for the scholarship if they belong to a household with no other member holding a college-graduate degree. Accordingly, we define an individual aged 17-22 as eligible for the FGGS scheme if none of their household members aged 23 years or older is a college graduate. Hence, our DiD analysis considers the sample of 35,184 eligible candidates in the 17-22 age group from Tamil Nadu, Karnataka, and Kerala.

We consider both unconditional and conditional enrollment in technical streams at the undergraduate level as our main outcomes of interest. First, using an individual's current enrollment status and the type of course, we create a binary outcome variable ("enrolled in technical course") that takes the value one if the individual has enrolled in a technical course at the undergraduate level and zero otherwise.[9] Consistent with the FGGS scheme and as explained in Section 2, technical streams include Engineering,

[6] Specifically, we use the 66th round NSS survey on "Employment and Unemployment" collected in 2009-10 and the 68th round NSS survey on "Employment and Unemployment" collected in 2011-12, which is also used for the educational outcome data for the respective years. For the year 2007, we have used the "Employment & Unemployment and Migration Particulars" schedule instead of the "Participation and Expenditure in Education" schedule from the 64th round survey collected in 2007-08, as this analysis now focuses on labour market outcomes.

[7] Specifically, we added the following datasets: PLFS (periodic labour force survey) for the years 2017-18 & 2018-19, conducted by the National Statistical Office (NSO) of India.

[8] Given the long duration since the labour market entry period in 2014 and to maintain consistency with the educational round data, we did not include the 61st round survey data on "Employment and Unemployment", which was collected in 2004-05. Additionally, we did not use data collected during or immediately after the COVID-19 pandemic in 2019.

[9] Since the scholarship program is only for an undergraduate degree, the outcome variable takes the value 0 for individuals studying certificate, diploma, or postgraduate courses.

Medicine, and Agriculture degrees. Approximately 8% of individuals in the sample are enrolled in such courses when we consider this unconditional enrollment as our outcome variable.

Next, we consider the choice of streams by individuals conditional on being enrolled in any course. Thus, our second outcome variable, "stream choice", is a binary indicator of whether an individual studies a technical stream (=1) or a non-technical stream (=0) at the undergraduate level. Considering this stream choice variable conditional on overall enrollment, we find that 23% of the individuals in the sample are pursuing a technical course.[10]

3.3 Labour market outcomes

The age group of 25–29 years is defined as the potential age for labour market entry. Similar to our analysis of education outcomes, among these individuals, we seek to identify those who were eligible for FGGS scheme during their undergraduate studies; therefore, we consider only those individuals coming from households where no other household member above this age group (i.e., aged 30 years or older) is a college graduate. Our DiD analysis for labour market outcomes includes a sample of 18,397 eligible candidates from Tamil Nadu, Karnataka, and Kerala.

To examine whether the effects of the policy extend to the labour market, we first assess individuals' educational attainment, specifically, the completion of a technical degree. Our primary outcome of interest is the binary variable "technical graduate", which takes the value of one if an individual aged 25–29 has completed an undergraduate degree in Engineering, Medicine, or Agriculture, and zero otherwise. We consider both unconditional and conditional graduation (i.e., stream choice) at the undergraduate level.

Labour market outcomes are analyzed across three dimensions: employment type, industry type, and occupation type, based on the individual's usual activity status.[11] First, we measure employment type using binary variables that categorize individuals' activity status into self-employment, regular employment, casual employment, seeking employment, and not being in the labour force. Self-employment includes individuals

[10] The summary statistics for the full sample and the conditional sample are reported in columns (1) and (2), respectively, of Table 1.

[11] Usual activity status, reflects the primary economic or non-economic activity undertaken during the 365 days preceding the survey. The usual principal activity status is assigned when an individual spends the majority of this period in a specific activity. Additionally, individuals who engaged in economic activities for at least 30 days within the same period are assigned a subsidiary economic activity status. We consider principal and subsidiary usual activity together to construct the labour market outcome variables.

working in a household enterprise as an own-account worker, employer, or unpaid family worker. Regular employment considers individuals in salaried or wage employment. Casual employment indicates if the person works as a casual wage labourer, either in public works or other types of work. Seeking employment includes individuals actively looking for work or available for work. Finally, the indicator of not being in the labour force identifies if the person is engaged in non-economic activities, such as education, domestic duties, collecting household goods, receiving pensions or remittances, or being unable to work due to disability.

Second, to analyze industry type, we use the National Industrial Classification (NIC) codes recorded in the survey to create three binary variables representing primary (agriculture), secondary (manufacturing), and service sectors.

Third, we further examine the occupation type of employed individuals using the National Classification of Occupations (NCO) framework. This classification considers educational and technical qualifications, job responsibilities, and task complexity to categorize occupations into elementary occupations (simple and routine physical or manual tasks), secondary occupations (tasks such as operating machinery and maintenance work), associate professionals (complex technical tasks requiring specialized knowledge), professionals (advanced problem-solving, decision-making, and creative tasks)[12], and leaders or executives (high-level decision-making and managerial roles)[13]. We construct binary variables for each category, assigning a value of one if the occupation of the employed individual falls within the respective category and zero otherwise. Table A.3 in the appendix summarizes the variables used to capture the labour market outcomes.

3.4 Other variables

We also examine additional outcome variables to explore potential channels through which the FGGS scheme may exert its influence, focusing on the complementary role of education loans, and educational expenditures as well as analyzing the scheme's social welfare implications.

The 2013 round of the NSS survey includes detailed household-level information on outstanding cash loans, including borrowing dates, purposes, loan amounts, and credit

[12] The occupation categories correspond to the four skill levels defined in the NCO. Skill levels are determined based on academic and technical qualifications, experience requirements, and the typical job description, reflecting whether the role entails administrative, managerial, or supervisory responsibilities or subordinate and repetitive tasks within the Indian context.

[13] Given the wide variation in skills required for certain occupations, such as Legislators, Senior Officials, and Managers, the concept of skill level was not applied to them, leading to their classification as 'undefined' by NCO.

agency details. Leveraging this dataset, we examine the impact of the FGGS scheme on education-related borrowing. Our analysis focuses on households with eligible candidates, defined as those with at least one individual aged 17–22 and no household members aged 23 or older who have completed a college degree.

We, then, transform this cross-sectional sample of first-generation college-going households in 2013 into a household-year panel by organizing education loan information by year. The resulting panel spans the period from 2005 to 2013 and captures, for each household-year, whether any educational loan was taken, the amount borrowed, and the breakdown by institutional and non-institutional credit sources. We treat the years 2005–2009 as the pre-treatment period and 2010–2013 as the post-treatment period. And, Tamil Nadu serves as the treatment state, while Karnataka and Kerala function as control states, consistent with the main analysis.

Our primary outcome in this data is a binary variable, education loan, which equals one if the household borrowed for education in a given year, and zero otherwise. Additionally, we also create the outcome variable education loan amount, in real terms, as a measure of the total annual amount borrowed for education.

In the educational outcomes data, only the 2007 and 2014 rounds contain detailed information on expenditure particulars for individuals currently enrolled in educational institutions.[14] We use these two rounds to examine changes in educational expenditure as a potential mechanism, with the 2007 round representing the pre-treatment period and the 2014 round representing the post-treatment period.

We construct a variable, course fee, which captures the total amount paid by a student enrolled in technical education. This includes tuition, examination, development fees, and other mandatory payments. We also define educational expenditure as the total amount spent on education, encompassing course fees and additional costs such as books, stationery, uniforms, transportation, private coaching, and other related expenses. All expenditure figures are adjusted to real terms to account for inflation. Additionally, we construct two proportion-based variables: share of educational expenditure and share of course fee. The former represents an individual's total educational expenses as a fraction of the household's total annual expenditure, while the latter denotes the course fee alone as a fraction of the same. A household's total annual expenditure is estimated by multiplying its usual monthly consumption expenditure by 12 and adding the household's annual expenditure on education.

[14] Specifically, we use the following rounds of NSS data: 64th round survey on "Participation and Expenditure in Education" collected in 2007-08, and 71st round survey on "Social Consumption: Education" collected in 2014.

We also analyze the social welfare implications of the FGGS scheme. All rounds of labour market data include information on household monthly expenditure. We create the variable monthly per capita expenditure (MPCE) by dividing the household's monthly expenditure by household size, measuring it both in real terms and as a log-transformed variable. Our analysis focuses on households with eligible candidates, defined as those with at least one individual aged 25–29 and no household members aged 30 or older who have completed a college degree (labour market sample).

4 Empirical strategy

In this section, we outline our empirical strategy to estimate the impact of the FGGS scheme. We first discuss the difference-in-differences (DiD) approach, along with an event study specification and the synthetic difference-in-differences (synthetic DiD) method, to analyze educational outcomes. We then describe the methodology for labour market outcomes.

4.1 Difference-in-differences (DiD)

We estimate the intent-to-treat (ITT) effect of the FGGS scheme by analyzing the status of technical course enrollment and stream choice in Tamil Nadu before and after the implementation of the scheme and comparing it with the neighbouring states of Kerala and Karnataka through a DiD framework. Our analysis considers the eligible candidates, as defined in Section 3.2, from Tamil Nadu as the treated group; the control group consists of individuals defined in the same way, from Kerala and Karnataka. The pre-treatment data come from the years 2004, 2007, and 2009, while the post-treatment data come from 2011, 2014, and 2017. We estimate the following equation separately for technical enrollment and stream choice outcomes:

$$Y_{idst} = \beta_0 + \beta_1 Post_t + \beta_2 TN_s + \beta_3 (Post_t \times TN_s) + \beta_4 X_{idst} + \mu_{ds} + \gamma_t + \epsilon_{idst} \tag{1}$$

Here, Y_{idst} is the outcome variable of interest, indicating enrollment in the technical degree courses for individual i, from district d, state s, and time t. The $Post$ dummy takes the value of 1 if the year is 2011 or later and zero if the year is before 2011. TN is a dummy that takes the value one if the i-th observation comes from Tamil Nadu, and otherwise, 0. β_3 is the causal estimate of the impact of FGGS on the outcome variables under the assumption of parallel trends, i.e., in the absence of the treatment, the temporal change in outcome would be same between Tamil Nadu and the control states. Other individual, household, village, and district characteristics that may affect the outcome variables are controlled by X_{idst}.[15] We also control for district and year-fixed effects (μ_{ds} and γ_t respectively) to account for the secular district and year-level changes that might affect the outcome variables. The standard errors are clustered at the district level.[16] Also, survey weights were included in our analysis.

4.2 Event study

We use a DiD event study, also known as the dynamic DiD model, as a robustness check. The event study shows the DiD estimates separately for different years and is given by Eq. (2):

$$Y_{idst} = \alpha + \sum_{t \neq 2009} \beta_t (TN_s \times Year_t) + \lambda X_{idst} + \mu_{ds} + \gamma_t + \epsilon_{idst} \tag{2}$$

Here all the variables are defined in the same way as in Eq. (1). The only change being, now the treatment variable (TN_s) is interacted with $Year_t$ indicating whether observation i belongs to year t, where $t \in \{2004, 2007, 2011, 2014, 2017\}$. The reference year for the analysis is 2009, the year just prior to the implementation of the treatment.

The event study analysis also allows us to test for pre-existing trends by conducting a joint significance test of the coefficients (β_t) corresponding to the pre-treatment periods; thus, it helps us to assess the assumption of parallel trends for identification in our DiD analysis.

4.3 Synthetic DiD

As an additional robustness check, we estimate the effect using the synthetic difference-in-differences method proposed by Arkhangelsky et al. (2021). In this method, the impact of the FGGS scheme is estimated by constructing a synthetic Tamil Nadu to represent the counterfactual state in a DiD framework. The synthetic DiD complements both the standard synthetic control method (SCM) and the difference-in-differences approaches.[17]

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[15] Household characteristics include the highest educational qualification of members (excluding potential candidates), religion, social category, and household size. Individual-level controls include age, sex, relationship to the household head, and marital status. We account for neighborhood effects using the sector of residence (rural or urban). At the district level, controls include the total number of colleges and the proportion of technical colleges.

[16] Even though the policy was implemented at the state level, the number of clusters is too small to cluster the standard errors at the state level (Cameron and Miller, 2015). To address this issue, we collapse the data at the state-year level and conduct a synthetic DiD analysis, as explained in Section 4.3.

[17] SCM constructs a counterfactual as a weighted average of comparison unit states. The SCM consists of a weighted regression with time-fixed effects but no unit-fixed effects (Abadie, 2021). The difference-

This method fits well with our aims as it also allows us to study the FGGS scheme's effects on potential Tamil Nadu candidates by constructing counterfactuals from the other states and during the pre-intervention period. The synthetic DiD method also relaxes the parallel trends assumption by constructing a weighted combination of control units that best replicate the pre-treatment trend of the treated group (Clarke et al., 2023).

For the synthetic DiD method, we create balanced state-level panel data by collapsing the individual-level data used in our main analysis.[18] While the individual is the unit of analysis in the DiD method, the synthetic DiD analysis considers the state as the unit of analysis. The analysis takes 18 large Indian states, including Karnataka and Kerala, in the donor pool to construct the control group. The panel has data for six years, from 2004 to 2017, spanning the period before and after the program implementation. Standard errors are based on pseudo-random placebo reshuffling, as suggested by Arkhangelsky et al. (2021) for a small number of treated units.

4.4 Methodology for labour market outcomes

The DiD model to estimate exposure to the FGGS program on labour market outcome is similar to Eq. 1. We use multiple binary outcome variables, as defined in Section 3.3, to measure educational attainment, employment type, industry type, and occupational type. Since eligible candidates of the FGGS started entering the labour market in mid-2014, as explained in Section 3.1, we consider this period as the beginning of the treatment period in the labour market sample. Hence, the post-treatment indicator ($Post$) equals one for the years 2017 and 2018 and zero for the years 2007, 2009, and 2011. All other variables are defined in the same way as in Eq. (1). We also employed the synthetic DiD method as an additional robustness check for labour market outcomes, following the approach outlined in Section 4.3.

5 Results

In this section, we start by presenting the impact of the FGGS scheme on technical course enrollment and stream choice. Then, we demonstrate the robustness of our results and

in-differences can be thought of as an unweighted regression with both time and unit fixed effects. The synthetic DiD estimator integrates these approaches by calculating weights for periods, with weights calculated to achieve a balance between pre- and post-program periods.

[18] We use survey weights to create the average values at the state-year level. Thus, our outcome variable in this analysis is the proportion of eligible candidates studying in technical courses and the proportion of such enrolled individuals choosing technical streams. Similarly, the control variables also capture the average characteristics of these individuals at the state level for a given year.

the heterogeneity of the impact of FGGS on education outcomes across socio-economic categories. After that, we examine the consequences of the FGGS scheme on labour market outcomes. Finally, we present evidence on potential channels explaining our findings, including education expenditures and the complementary role of education loans. Additionally, we present suggestive evidence on the social welfare implications of the FGGS scheme.

5.1 Main results on technical course enrollment and stream choice

We present the estimates of the effect of FGGS scheme on technical course enrollment and stream choice, using DiD and synthetic DiD methods, in Table 2.[19] For the DiD model, we begin with a basic specification controlling for individual and household level factors and then gradually add fixed effects to account for unobserved characteristics at the state and district levels, as well as year fixed effects to control for secular changes in the outcome over time. Across different specifications, we find a statistically significant and positive effect of the FGGS scheme on enrollment in technical courses (columns 1-3) and the choice of technical streams compared to non-technical streams (columns 5-7). In response to the policy, technical course enrollment increased by around 3.7 percentage points, which translates to around 123% of the mean outcome. Similarly, the impact on stream choice is 8 percentage points or 59% over the mean outcome. The estimates are also quite stable across different specifications.

To assess if there were any differential trends between the treated and control group of states prior to the treatment, we rely on the event study analysis specified by Eq. (2), the results of which are discussed in greater detail in the next Section 5.2.1. The last row of Table 2 provides the p-value of the joint significance test of the DiD coefficients corresponding to the pre-treatment periods; they indicate no significant difference in technical enrollment and stream choice trends between treated and control groups before the policy intervention (p-values ranging from 0.162 to 0.994), suggesting that the parallel trends assumption holds for our DiD analysis.[20]

Furthermore, the results from the synthetic DiD analysis confirm the positive and statistically significant impact of the FGGS scheme on both technical course enrollment (Column 4) and stream choice (Column 8). The estimated effect on technical course enrollment is 0.042, and on stream choice, it is 0.085. These estimates suggest that, in

[19] The expanded version of Table 2 reporting the coefficients for each of the demographic variables from the DiD model is presented in Table A.16.

[20] Additionally, we conducted a test of pre-existing trends using data for only the pre-intervention period, i.e., limiting the sample of analysis to the years 2004 and 2007. This test also shows that the pre-regulation coefficients are jointly insignificant. These results are not shown but are available on request.

the absence of the FGGS scheme, the technical course enrollment rate in Tamil Nadu would have been approximately 4.2 percentage points lower, and the choice of technical courses over non-technical courses would have been 8.5 percentage points lower than the synthetic control state of Tamil Nadu. These estimates align closely with the results from the DiD approach, reinforcing the robustness of our findings.

5.2 Robustness checks

We conduct additional robustness checks, including event studies, placebo tests, and alternate samples with border districts.

5.2.1 Event study

The results of the event study analysis for technical enrollment and stream choice are presented in Figure 1 and Table A.4. The figure displays the coefficients derived from Eq. (2), estimating the impact of the FGGS scheme over time. Specifically, it shows the year-by-year effects for 2004, 2007, 2011, 2014, and 2017, with 2009 (which is immediately before the year of intervention) as the base year. In both panels of the figure, the DiD coefficients for the years prior to the intervention, i.e., 2004 and 2007, are not statistically different from zero, indicating that there were no differential trends in technical enrollment or stream choice between Tamil Nadu and the control states during the pre-intervention period. In contrast, the post-intervention period (2011, 2014, and 2017) shows significant positive coefficients for both technical enrollment and stream choice. These results suggest that the FGGS scheme had a meaningful impact on increasing access to technical education and encouraging first-generation students to shift from non-technical to technical courses. A formal joint significance test further confirms that the pre-intervention coefficients are not statistically significant, indicating an absence of differential trends prior to the program's implementation.[21]

5.2.2 Placebo tests

We conduct placebo tests by sequentially restricting the sample to different rounds (years) of data, starting from 2004, and assigning pseudo-implementation years. The first iteration includes 2004 and 2007, with 2007 as the pseudo-implementation year. Each subsequent iteration adds a year, designating the latest as the pseudo-implementation year (e.g., 2009 in the second iteration, 2011 in the third). Since the actual treatment began

[21] The p-values from this test are included in the last row of Table 2, as already mentioned above in Section 5.1.

in 2010, all years after 2010 are considered treated in subsequent iterations. Accordingly, 2011 and 2014 are assigned as implementation years in the fourth iteration, and 2011, 2014, and 2017 in the fifth and final iteration.

Figure A.2 presents estimated coefficients for technical enrollment (Panel A) and stream choice (Panel B). The results show that estimates for 2007 and 2009 are insignificant, while those for actual treatment years are positive and statistically significant. These findings, along with the event study, confirm the absence of significant pre-treatment trends, strengthening our causal inference.

5.2.3 Border districts

Our main DiD analysis considers neighbouring states as control states, considering their geographical proximity and socio-economic similarities to the treatment state. However, regions within the control (treatment) states that are farther from the treatment (control) state may not be comparable, potentially introducing bias. To address this concern, we conduct a subsample analysis restricted to the border districts of both the treatment and control states. This refinement reduces the sample size to 11,959 for the full sample and 4,269 for the conditional sample, covering 26 districts: 11 in Tamil Nadu, 7 in Karnataka, and 8 in Kerala.

A potential concern with using the border district subsample is the risk of spillover effects, as individuals residing in control-state border districts might enrol in the treatment state to access the FGGS scheme. However, program eligibility requires applicants to obtain certification from bureaucratic authorities in the treatment state, which mandates residency. This constraint minimizes spillover effects, making the border district subsample a more suitable robustness check for our study. The regression results, presented in Table A.5, confirm that even after restricting the sample to bordering districts, our findings remain consistent with the original estimates, reinforcing the robustness of our analysis.

5.3 Heterogeneous effects on educational outcomes

Next, we investigate whether the impact of FGGS on first-generation college students' educational outcomes varies by gender, religion, social group, education status of the family, and rural vs. urban sector. Intergenerational educational persistence and mobility patterns vary across social groups (Hnatkovska et al., 2013; Emran et al., 2023), with higher risks of downward mobility being found particularly among Scheduled Castes (SCs) and Scheduled Tribes (STs) compared to non-SC/ST individuals (Motiram and Singh, 2012). Gender and caste-based disparities in science education – driven by socioeconomic constraints, limited access to quality schooling, and false beliefs – limit disadvantaged groups' participation in STEM fields (Kumar and Sahoo, 2024). While some equalization of educational attainment has occurred across caste groups at the primary level, significant disparities persist in college education (Desai and Kulkarni, 2008). Despite this, the intersectionality of first-generation status with other social identities, such as caste, gender, and rural background, remains understudied.

To analyze the heterogeneity of the DiD estimates, we re-estimate Eq. (1), interacting the relevant heterogeneity variable with all the variables on the right-hand side of the equation, following the suggestion of Feigenberg et al. (2023). The heterogeneous effects by gender, religion, social categories, education status of the household, and sector (rural/urban) are presented in Figures 2–3. The corresponding estimates are also shown in Appendix Tables A.6–A.10.

The results presented in Figure 2 reveal that male students benefit more from the program compared to their female counterparts. The estimates presented in Table A.6 show that the gender difference in the treatment effect is statistically significant; across different specifications, the effect of FGGS scheme on girls' probability of technical course enrollment is positive but significantly lower than that of boys, while the effect on stream choice for girls are statistically not significant (Table A.11). The results also reveal that the FGGS scheme has a significant positive effect on first-generation Hindu students, while the effects on other religious groups are not statistically significant.[22] Considering social groups, OBC students exhibit positive and statistically significant gains in both outcomes, while policy had a statistically significant impact on stream choice among ST students.

The results presented in Figure 3 further reveal that first-generation students benefit more from the policy when they belong to households where the highest level of education of any member is secondary level or below. Also, students from urban areas tend to reap greater benefits from the policy. The program has a differential impact across social categories. One reason for this is that technical courses are generally more expensive than non-technical courses. Without universal free education or a full fee waiver, technical courses remain inaccessible to many. Since the FGGS covers only a portion of the total expenses for technical education, the costs may still be unaffordable for some households, even after a tuition fee waiver. In Section 5.5, we discuss how the FGGS affected household educational expenditure and how education loans function as a complementary funding mechanism that enables households to afford technical education.

[22] The non-significance on other religious groups might be driven by lower sample size.

5.4 Labour market outcomes

Changes in enrollment and choice of streams towards technical courses at the undergraduate level may have labour market consequences. The first cohort of students potentially benefiting from the policy would have completed their undergraduate education in 2014 for four-year courses (engineering and agriculture) and in 2016 for six-year courses (medical courses). We conduct the DiD and synthetic DiD analysis considering individuals aged 25-29 years and defining the post-intervention period for labour market outcomes accordingly, as explained in Section 4.4. We focus on educational attainment (graduation in technical streams) and early labour market outcomes, including the types of employment, industry, and occupation as our outcomes of interest.

5.4.1 Educational attainment

While our previous analysis shows that FGGS scheme led to an increase in enrollment in technical courses, it remains an open question whether the beneficiary students completed these courses. Therefore, the first outcome in the labour market sample is the likelihood of graduating with a technical degree and, conditional on graduation, the probability of having a technical versus a non-technical degree (i.e., stream choice).

Table 3 presents the estimated impacts of the FGGS scheme on educational attainment, using both DiD and synthetic DiD models. Column (1) reports the effect on technical graduation, while Column (2) shows the effect on stream choice. We find a statistically significant and positive effect of the FGGS scheme on educational attainment. Specifically, the DiD estimates show that exposure to the scheme increased the likelihood of technical course graduation by 3.6 percentage points (Column 1). Similarly, the FGGS scheme increased the likelihood of choosing technical streams, as opposed to non-technical streams, by approximately 9.4 percentage points (Column 2), with both estimates being statistically significant at the 1% level. The synthetic DiD analysis further confirms these findings, reporting a treatment effect of 0.048 for graduation and 0.150 for stream choice. These results imply that, in the absence of the FGGS scheme, graduation in technical course and technical stream choice rates in Tamil Nadu would have been approximately 4.8 and 15 percentage points lower, respectively, than those observed in the synthetic control state.[23]

[23] We present the results separately for the male and female samples in Table A.12. Consistent with the heterogeneous effects found for technical course enrollment, we find a higher point estimate for educational attainment among males, compared to females, in the labour market sample.

5.4.2 Type of employment

We now turn to examine the effects of the FGGS scheme on employment types. Columns 4-7 of Table 3 report results across five employment categories: self-employment, regular salaried employment, casual labour, job-seeking or availability for work, and being out of the labour force.

Overall, we find that the program led to an increase in regular salaried work and a decline in casual labour. Both DiD and synthetic DiD estimates show a statistically significant increase in regular employment. The DiD estimate shows that the beneficiaries of the FGGS scheme were about 4.3 percentage points more likely to secure regular employment compared to their non-beneficiary counterparts, implying a 21% increase in the probability of regular employment over the mean. The point estimate from the synthetic DiD model is somewhat larger. Additionally, the coefficient on casual labour is negative and statistically significant in the synthetic DiD analysis, indicating a reduction in engagement with casual labour among the treated individuals.

Interestingly, the scheme also increased the availability of work or seeking employment by five percentage points (Column 6). The synthetic DiD analysis also shows a positive effect, albeit statistically not significant. We do not find any significant effects on self-employment or labour force non-participation, indicating that the program's primary labour market impact arises through the choice of different types of employment rather than labour force participation at the extensive margin.

5.4.3 Type of industry

The effects of the FGGS scheme on individuals' choice of industry, conditional on being employed (in self-employment, regular, or casual work), are presented in Table 4. The results indicate significant changes in the type of industry individuals are employed, because of the FGGS scheme. The DiD estimates show a statistically significant decline of 7.1 percentage points in the likelihood of employment in the agriculture sector (Column 1), while the likelihood of working in the service sector increased by 6.7 percentage points (Column 3), significant at the 5% level. The impact on the secondary (manufacturing) sector is statistically insignificant (Column 2). The synthetic DiD analysis also reveals a significant increase in the likelihood of employment in the service sector by 12.5 percentage points (Column 3). These results suggest that technical education acquired through the program facilitated transitions into more formal or organized employment opportunities, especially in the service sector.

5.4.4 Type of occupation

We also analyze the effects of the FGGS scheme on the occupational choices of individuals engaged in self-employment, regular employment, or casual work. The results are presented in columns (4) to (8) of Table 4. The FGGS scheme significantly increased the likelihood of employment in associate professional roles by 3.9 percentage points (statistically significant at the 5% level) according to the DiD model, and by 10.1 percentage points according to the synthetic DiD model, statistically significant at the 1% level (Column 5). We also find evidence of positive effects on the take-up of secondary occupations (3-4 percentage points) and professional occupations (7-8 percentage points); across the two methods, the magnitude of the estimates remains largely similar, although the precision varies in this case. These findings suggest that the program enabled first-generation graduates to access occupations associated with higher skills and white-collar jobs, reflecting upward occupational mobility.[24]

5.5 Mechanisms and implications

Complementary education loan: Technical courses like Engineering, Medicine, and Agriculture are expensive in India. The FGGS scheme waives tuition fees, but students must still cover other expenses such as examination fees, library charges, and hostel accommodation. Also, many students relocate to pursue higher education, incurring additional costs for food, travel, and housing, which are especially challenging for first-generation students. Educational loans are a critical resource for financing these residual costs. Technical courses such as Engineering, Medicine, and Agriculture are often prioritized for loan approvals, with eligibility depending on the reputation of the institution and the applicant's admission to an approved program. Repayment typically begins one year after graduation or six months after securing employment, whichever comes earlier. This makes educational loans offered through institutional channels a suitable complementary funding mechanism for higher education. Hence, we expect that with FGGS enabling more first-generation students to enroll in technical courses, their reliance on educational loans to supplement the tuition waiver is likely to have increased.

We estimate the likelihood of households taking an education loan with a binary variable in a DiD framework. Additionally, we employ a Tobit model within the same framework to estimate the annual amount borrowed for education (in real values). Table 5 presents the estimated impact of the First Generation Graduate Scheme (FGGS) on

[24] Tables A.12-A.13 show the gender-disaggregated estimates for the types of employment, industry, and occupation. We find that the effects are largely driven by the male sample.

educational loan acquisition among first-generation households. DiD estimate indicates that these households were 2.8 percentage points more likely to obtain an education loan due to the FGGS, a statistically significant effect at the 1% level (Column 1). Additionally, the Tobit model estimates also reveal the increase in the loan amount borrowed for education because of the FGGS scheme (Column 2).[25] Panel B focuses on education loans from institutional lenders, showing a similar trend. The likelihood of borrowing increased by 2.1 percentage points, and the Tobit estimates suggest a significant increase in the real loan amount. Panel C examines loans from non-institutional lenders, where the likelihood of borrowing increased only by 0.9 percentage points, with no statistically significant changes in the loan amount. This suggests that while FGGS reduces the financial burden, loans likely play a complementary role in enabling students to afford the full cost of their higher education. Also, institutional lenders played a major role in financing first-generation students' educational costs.

Expenditure on technical degree education: Given that first-generation students are enrolled in college with tuition fee waivers, their education expenditure should be less in the treatment state compared to the first-generation students enrolled in the control states. Since the FGGS scheme directly transfers tuition fees – a component of the overall course fees – on behalf of students to colleges, we expect that students enrolled in technical courses under the scheme would have lower out-of-pocket expenses and course fees compared to their peers. Hence, we study the impact of the FGGS scheme on the education expenditures of the individuals who enrolled in technical courses. The results in Table 6 suggest that the FGGS scheme effectively reduced the proportion of household resources allocated to technical education. Both education expenditure and course fees, as a share of total household spending, declined by 10 percentage points.

Social welfare: Our analysis of labour market returns reveals notable shifts in employment type, industry, and occupation. These transformations have significant implications for social welfare. Table 7 presents the estimated impact of the FGGS Scheme on Monthly Per Capita Expenditure (MPCE), a key indicator of social welfare. Both the DiD and synthetic DiD estimates reveal a significant and positive increase in MPCE following the implementation of the FGGS scheme.

[25] The amount borrowed for education increased by approximately Rs. 70635 in real terms, which is 90% higher than the average amount of education loan taken (Rs 78516). We observed a similar effect while using the log-transformed value of the loan amount.

6 Conclusion

This study sheds light on the effects of targeted policies for first-generation college students, particularly in the context of a developing country. Using the DiD and synthetic DiD approach, and data from the National Sample Survey (NSS), we evaluate the impact of the First Generation Graduate Scholarship (FGGS) scheme in Tamil Nadu, which provides full tuition fee waivers for FGCS pursuing technical courses.

Our findings reveal that the FGGS scheme significantly increased technical course enrollment and shifted students from non-technical to technical streams. By directly addressing the affordability of tuition fees, the program enabled FGCS to access technical education that would have otherwise been financially prohibitive.

We find suggestive evidence that the FGGS scheme led to lower education expenditures for students enrolled in technical courses in Tamil Nadu. However, even with the tuition fee waiver, technical education in fields like Engineering, Medicine, and Agriculture remains expensive, prompting families to rely heavily on education loans. The program increased reliance on institutional credit to cover residual costs. Previous research highlights that merely increasing the supply of educational loans is insufficient without addressing demand-side barriers (Chandrasekhar et al., 2019). By mitigating financial barriers/risks, the tuition fee waiver helped FGCS utilize educational loans more effectively.

Tuition fees are charged every semester, while the tuition fee waiver is provided directly to colleges as an annual subsidy. This arrangement creates an incentive for colleges to retain students throughout the duration of their programs. Combined with students' own motivation to complete their degrees, this incentive structure appears to have positively influenced program completion rates. Our findings indicate that the FGGS scheme led to a significant increase in technical degree completion rates.

In terms of labour market outcomes, the program influenced a shift toward service-sector employment and increased participation in associate-level skilled jobs. While it reduced casual labour participation and increased the likelihood of regular employment, the program also led to an increase in the number of FGCS seeking work or unemployment. This may reflect heightened aspirations among graduates, who are either waiting for better job opportunities or preparing for public-sector exams (Mangal, 2024). This raises concerns about whether the FGGS program has created a mismatch between the supply of technical graduates and the availability of suitable jobs (Kelley et al., 2024).

We also observed an increase in monthly per capita expenditure (MPCE) among FGGS recipients following the program's implementation, suggesting an improvement in household living standards. However, the absence of detailed income data limits a deeper evaluation of the program's impact on earnings and economic mobility.

We also find heterogeneity in the program's impact, reflecting underlying inequalities in opportunities and aspirations across different groups. For instance, women experience smaller gains than men, a pattern that mirrors persistent gender gaps in intergenerational mobility in India (Asher et al., 2024). A similar disparity has also been found in England, where first-generation college women earn less than their peers with graduate parents, while no such gap exists for men, highlighting gendered barriers to upward mobility (Adamecz-Völgyi et al., 2023). The relatively greater benefits observed for male students suggest that they are better positioned to capitalize on the opportunities enabled by the FGGS scheme. This could be due to lower aspirations among female participants compared to their male counterparts (Sarkar et al., 2020), cultural norms, and gendered expectations further constraining women's educational and occupational choices (Jayachandran, 2015). It also shows that a more targeted approach might be needed to address existing gender gaps in technical education (Sahoo and Klasen, 2021) and labour force participation rates (Klasen and Pieters, 2015; Sarkar et al., 2019). Thus, differential impact of the FGGS scheme across various groups suggests a need for intersectional approaches that account for overlapping social identities, such as first-generation status, caste, gender, and geography, to design more inclusive policies.

A notable limitation of this study is that it captures only the intent-to-treat effect due to data constraints. The inability to identify actual beneficiaries of the scheme restricts the scope of analysis. Additionally, the absence of control groups within Tamil Nadu, where the policy effectively operates as a near-universal program due to the prevalence of first-generation students, limits the scope of comparative analysis.

The FGGS scheme represents a significant step toward fostering social equity in higher education. By alleviating financial barriers and enhancing access to technical courses, the program holds the potential to transform the lives of first-generation students and contribute to broader economic development. However, challenges such as the slow absorption of technical graduates into the labour market and the disproportionate concentration of benefits among specific subgroups highlight the need for complementary policy reforms to amplify its impact.

The magnitude of the social return to education is crucial for evaluating the efficiency of public investment in education. We expect that the FGGS program would have increased the wages of its beneficiaries. An increase in the supply of college graduates typically raises their wages (Moretti, 2004), and estimated returns to education are generally higher in developing countries than in industrialized nations (Duflo, 2001). However, due to data limitations, we were unable to explore the social returns of the FGGS program in detail.

Moreover, the consequences of higher education interventions extend beyond labour market outcomes. Krueger and Lindahl (2001) argue that expanding human capital at higher education levels generates spillover benefits, such as technological progress and higher productivity. Investigating these broader effects will be the focus of future research.

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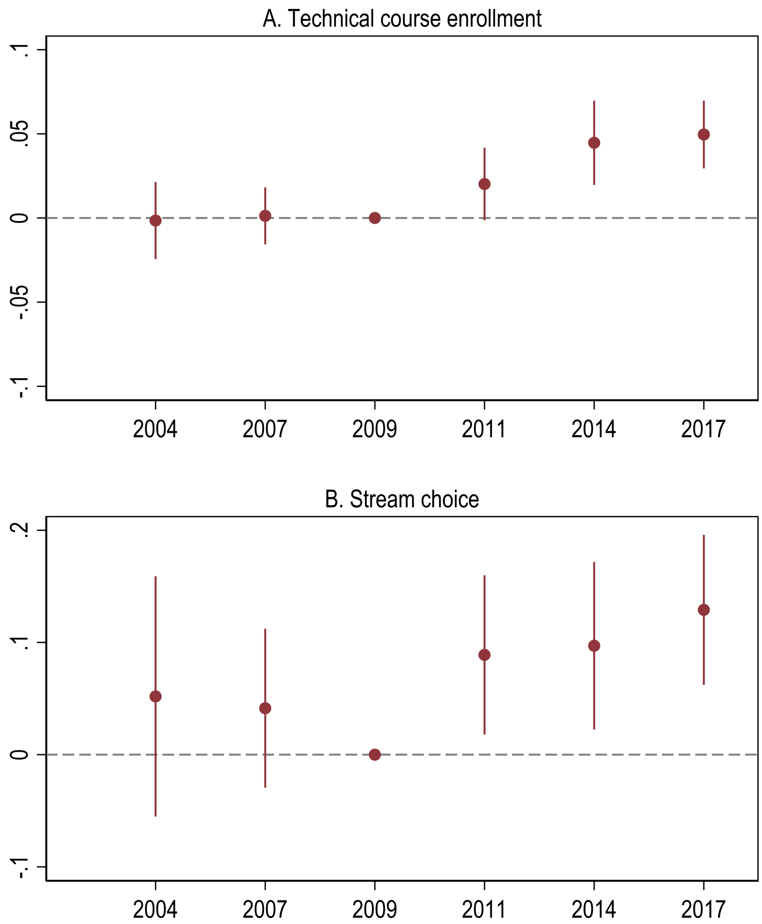
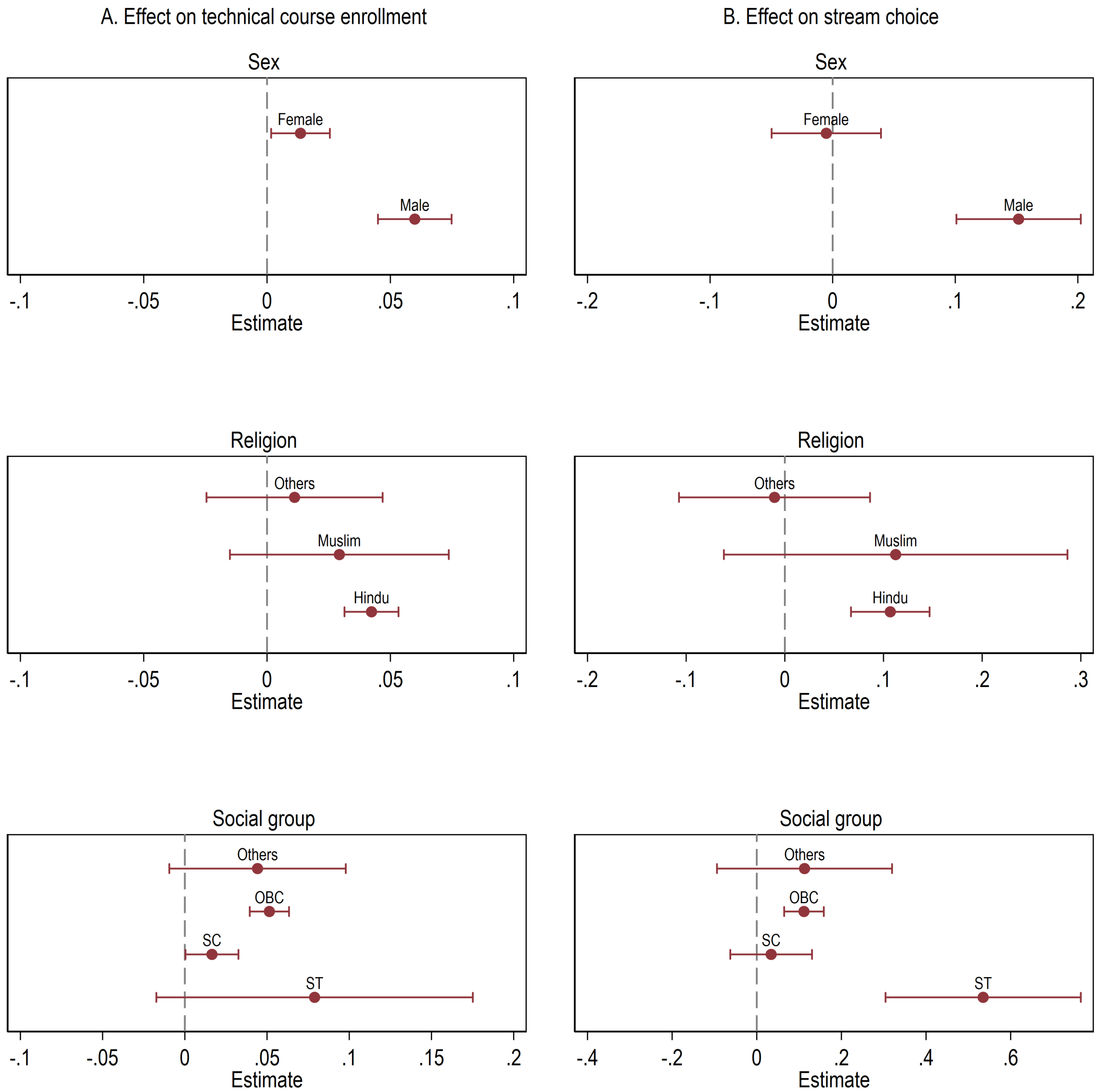
Figures and Tables

Figure 1: Event study analysis for technical course enrolment



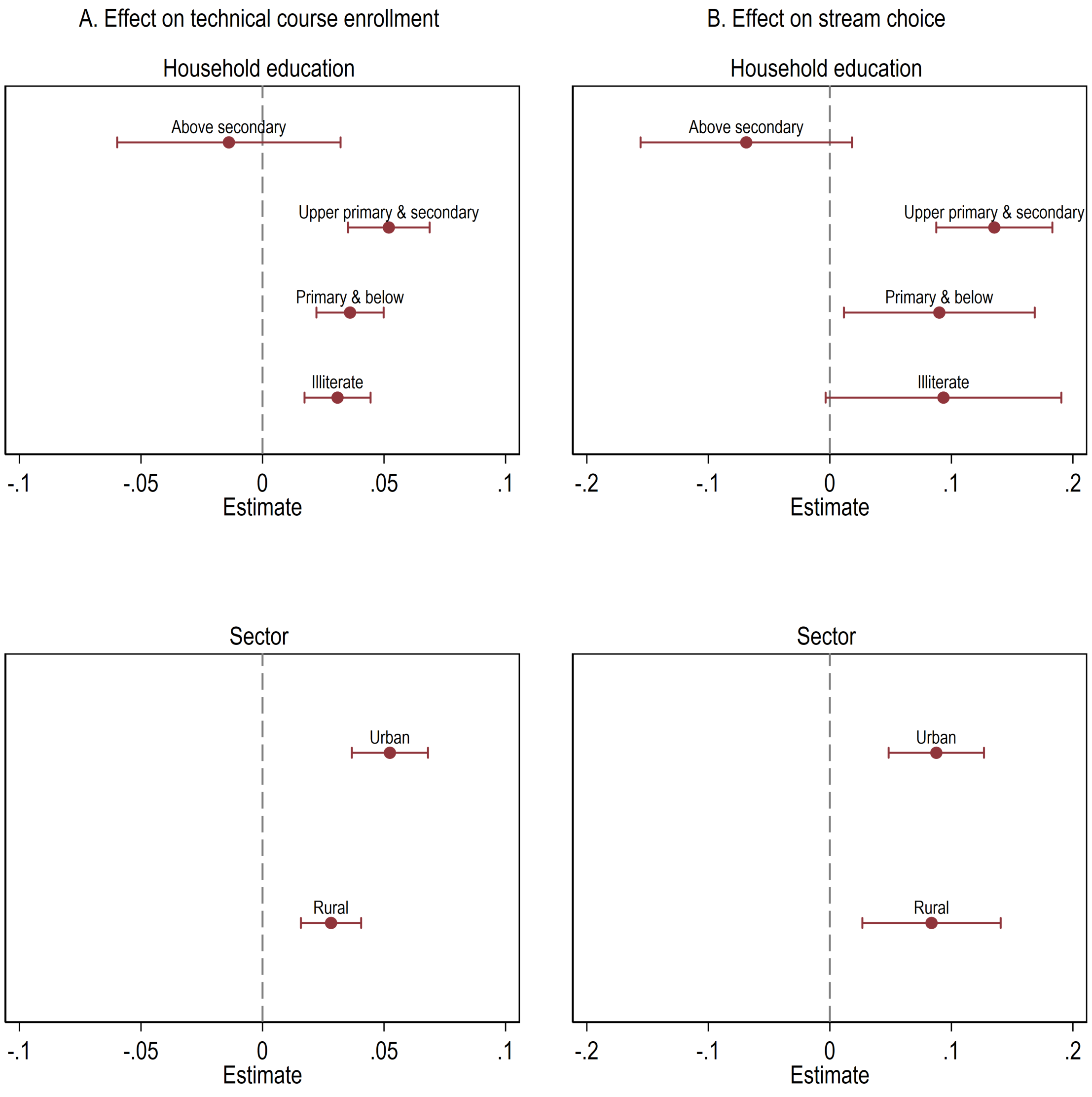
Notes: The figure illustrates event study plots for educational outcomes, using data from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The upper panel presents the event study coefficients for technical course enrollment, while the lower panel displays the coefficients for stream choices. The dot points represent the year-specific coefficients derived from the regressions of the outcome variable, and the vertical lines on the points depict the 95% confidence intervals. The year 2009 serves as the omitted category. Each regression includes control variables such as sex, age, marital status, caste and religion, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. The model also accounts for year and district-fixed effects. Standard errors are clustered at the district level, and observations are weighted using NSS sampling weights.

Figure 2: Heterogeneity in the effect of FGGS on technical course enrollment and stream choice by sex, religion, and social group



Notes: The figure illustrates the heterogeneous impact of FGGS on the educational outcomes of first-generation students. Using data from NSS rounds corresponding to years 2004, 2007, 2009, 2011, 2014, and 2017, Column (a) highlights the differential impacts by gender, religion, and social groups on technical course enrollment, while Column (b) illustrates the differential impacts on stream choice. Point estimates are represented by dots, with lines indicating 90% confidence intervals. Each regression includes control variables such as sex, age, marital status, caste and religion, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. The model also accounts for year and district-fixed effects. Standard errors are clustered at the district level, and observations are weighted using NSS sampling weights.

Figure 3: Heterogeneity in the effect of FGGS on technical course enrollment and stream choice by parent education and sector



Notes: The figure illustrates the heterogeneous impact of FGGS on the educational outcomes of first-generation students. Using data from NSS rounds corresponding to years 2004, 2007, 2009, 2011, 2014, and 2017, Column (a) highlights the differential impacts of household education (the highest education of the household) and gender on technical course enrollment, while Column (b) illustrates the differential impacts on stream choice. Point estimates are represented by dots, with lines indicating 90% confidence intervals. Each regression includes control variables such as sex, age, marital status, caste and religion, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. The model also accounts for year and district-fixed effects. Standard errors are clustered at the district level, and observations are weighted using NSS sampling weights.

Table 1: Summary statistics for educational outcomes

	Full Sample				Enrolled Sample			
	Mean (1)	Std Dev (2)	Min (3)	Max (4)	Mean (1)	Std Dev (2)	Min (3)	Max (4)
Individual level variables								
Technical course enrollment	0.03	0.17	0	1	0.14	0.35	0	1
Female	0.49	0.50	0	1	0.45	0.50	0	1
Age 17 years	0.16	0.36	0	1	0.12	0.33	0	1
Age 18 years	0.20	0.40	0	1	0.28	0.45	0	1
Age 19 years	0.14	0.35	0	1	0.24	0.43	0	1
Age 20 years	0.21	0.41	0	1	0.22	0.41	0	1
Age 21 years	0.13	0.33	0	1	0.09	0.28	0	1
Age 22 years	0.17	0.37	0	1	0.06	0.23	0	1
Relation to household head								
Household head	0.00	0.06	0	1	0.00	0.01	0	1
Unmarried child	0.74	0.44	0	1	0.91	0.29	0	1
Other relations	0.25	0.43	0	1	0.09	0.29	0	1
Household level variables								
Household xize	4.88	1.99	2	24	4.49	1.54	2	19
Social category								
Scheduled Tribe	0.04	0.19	0	1	0.02	0.14	0	1
Scheduled Caste	0.21	0.41	0	1	0.16	0.37	0	1
Other Backward Class	0.60	0.49	0	1	0.65	0.48	0	1
Other social group	0.15	0.35	0	1	0.17	0.37	0	1
Religion								
Hindu	0.80	0.40	0	1	0.79	0.41	0	1
Muslim	0.15	0.36	0	1	0.11	0.32	0	1
Other religions	0.05	0.23	0	1	0.10	0.29	0	1
Highest education of the household								
Illiterate	0.20	0.40	0	1	0.09	0.29	0	1
Primary & below	0.25	0.44	0	1	0.18	0.39	0	1
Upper primary & secondary	0.42	0.49	0	1	0.51	0.50	0	1
Above secondary	0.13	0.34	0	1	0.21	0.41	0	1
Other variables								
No. of colleges	56.31	82.54	0	441	58.05	79.60	0	441
Proportion of technical colleges	0.57	0.16	0	1	0.57	0.14	0	1
TN	0.41	0.49	0	1	0.48	0.50	0	1
Post	0.49	0.50	0	1	0.61	0.49	0	1
Rural	0.66	0.47	0	1	0.59	0.49	0	1
Urban	0.34	0.47	0	1	0.41	0.49	0	1
Observations	35184				11699			

Notes: The Enrolled in technical course variable is defined as a binary indicator for whether an individual has enrolled in a graduate degree program in engineering, medicine, or agriculture. Data is sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The full sample consists of individuals aged 17–22 from first-generation households in three states: Tamil Nadu, Kerala, and Karnataka. The enrolled sample is further restricted to individuals who are currently enrolled in undergraduate courses.

Table 2: Effect of FGGS scheme on technical course enrolment

	Technical Course Enrollment				Stream Choice			
	DID			Synthetic DID	DID			Synthetic DID
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TN × Post	0.038***	0.037***	0.037***	0.042***	0.084***	0.079***	0.081***	0.085***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.021)	(0.022)	(0.021)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	-	No	Yes	No	-
District FE	No	No	Yes	-	No	No	Yes	-
Year FE	No	Yes	Yes	-	No	Yes	Yes	-
Mean Dep Variable	0.031	0.031	0.031	0.017	0.143	0.143	0.143	0.102
Observations	35184	35184	35184	108	11699	11699	11699	108
Pre-trends test p-value	0.483	0.994	0.956	-	0.162	0.348	0.383	-

Notes: This table reports the coefficients from the DiD and Synthetic DiD specifications. The dependent variable indicates whether an individual has enrolled in a graduate degree program in engineering, medicine, or agriculture (Technical Course Enrollment) or chosen a technical stream while enrolled in an undergraduate course (Stream Choice). Data are sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The sample consists of individuals aged 17–22 from first-generation households in Tamil Nadu, Kerala, and Karnataka in columns (1)–(3). And it is further restricted to individuals currently enrolled in a graduate course in columns (5)–(7). Control variables such as sex, age, marital status, caste, religion, the highest education level of a family member, household size, the number of colleges in the district, and the proportion of technical colleges in the district. Columns (4) and (8) report results from the Synthetic DiD method, where state-level panel data are created by aggregating individual-level data over six years across 18 states. Standard errors are clustered at the district level for DiD estimates. For Synthetic DiD estimates, placebo-method standard errors are used. Observations are weighted using NSS sampling weights. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. A detailed version of the DiD table is provided in appendix A.16.

Table 3: Effect of FGGS scheme on educational attainment and employment type

	Educational Attainment		Employment Type				
	Technical Graduation (1)	Stream Choice (2)	Self Employed (3)	Regular Employee (4)	Casual Labour (5)	Available for Work (6)	Not in Labour Force (7)
Panel A - (DiD Model)							
TN × Post	0.036***	0.094***	0.015	0.043*	-0.038	0.050***	-0.036
	(0.006)	(0.026)	(0.023)	(0.023)	(0.024)	(0.013)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.027	0.136	0.180	0.205	0.181	0.083	0.377
Observations	14375	2674	18397	18397	18397	18397	18397
Pre-trends test p-value	0.064	0.046	0.984	0.475	0.466	0.645	0.658
Panel B - (Synthetic DiD Model)							
TN × Post	0.048***	0.150***	0.003	0.140**	-0.099*	0.023	-0.009
	(0.009)	(0.055)	(0.065)	(0.058)	(0.056)	(0.020)	(0.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.009	0.053	0.317	0.156	0.204	0.043	0.380
Observations	72	72	90	90	90	90	90

Notes: This table reports the coefficients from the DiD and Synthetic DiD specifications. The dependent variables for educational attainment indicate whether an individual has completed graduation in a technical course such as engineering, medicine, or agriculture (Technical graduation) and chosen a technical stream conditional on graduation (Stream Choice). The dependent variables for type of employment are binary variables derived from the individual's activity status. Data are sourced from NSS and PLFS rounds for the years 2007 (not for first-order outcomes), 2009, 2011, 2017, and 2018. The sample consists of individuals aged 25–29 from first-generation households in Tamil Nadu, Kerala, and Karnataka (Column 1). And it is further restricted to those individuals who have completed graduation in any course in column 2. Control variables include sex, age, marital status, caste, religion, the highest education level of a family member, household size, the number of colleges in the district, and the proportion of technical colleges in the district. Panel B reports results from the Synthetic DiD method, where state-level panel data are created by aggregating individual-level data over six years across 18 states. Standard errors are clustered at the district level for DiD estimates. For Synthetic DiD estimates, placebo-method standard errors are used. Observations are weighted using NSS sampling weights. The symbols ***, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The detailed version of the DiD table at appendix A.18.

Table 4: Effect of FGGS scheme on industry type and occupation type

	Industry Type			Occupation Type				
	Agriculture Sector (1)	Secondary Sector (2)	Service Sector (3)	Professionals (4)	Associate Professionals (5)	Secondary Occupations (6)	Elementary Occupations (7)	Others (8)
Panel A - (DiD Model)								
TN × Post	-0.071**	0.016	0.067**	0.025	0.039**	0.068*	-0.043	-0.062***
	(0.035)	(0.033)	(0.030)	(0.017)	(0.016)	(0.041)	(0.037)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.266	0.336	0.425	0.059	0.066	0.536	0.246	0.118
Observations	10530	10530	10530	10530	10530	10530	10530	10530
Pre-trends test p-value	0.358	0.278	0.206	0.238	0.697	0.105	0.972	0.016
Panel B - (Synthetic DiD Model)								
TN × Post	0.003	-0.100	0.125**	0.041**	0.101***	0.081	-0.110	-0.025
	(0.068)	(0.109)	(0.056)	(0.016)	(0.026)	(0.103)	(0.112)	(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.452	0.309	0.322	0.044	0.040	0.638	0.293	0.056
Observations	90	90	90	90	90	90	90	90

Notes: This table reports the coefficients from the DiD and Synthetic DiD specifications. The dependent variables are binary indicators representing the type of industry in which an individual is employed and the occupation type of the employment. Data are sourced from NSS and PLFS rounds for the years 2007, 2009, 2011, 2017, and 2018. The sample consists of employed individuals aged 25–29 from first-generation households in Tamil Nadu, Kerala, and Karnataka. Control variables include sex, age, marital status, caste, religion, the highest education level of a family member, household size, the number of colleges in the district, and the proportion of technical colleges in the district. Panel B reports results from the Synthetic DiD method, where state-level panel data are created by aggregating individual-level data over six years across 18 states. Standard errors are clustered at the district level for DiD estimates. For Synthetic DiD estimates, placebo-method standard errors are used. Observations are weighted using NSS sampling weights. The symbols ***, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The detailed version of the DiD table at appendix A.18 and A.19.

Table 5: Effect of FGGS scheme on education loan

	Education Loan (1)	Education Loan Amount(Tobit) (2)
Panel A - Overall Education Loan		
TN × Post	0.028***	70635**
	(0.006)	(30353)
Mean Dep Variable	0.017	1370
Observations	33136	33136
Panel B - Education Loan From Institutional Lender		
TN × Post	0.021***	86166**
	(0.004)	(39244)
Mean Dep Variable	0.012	1005
Observations	33136	33136
Panel C - Education Loan From Non-Institutional Lender		
TN × Post	0.009***	38636
	(0.003)	(49833)
Observations	33136	33136
Mean Dep Variable	0.006	338
Controls	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes

Notes: The dependent variable, Education Loan (Column 1), is a binary variable that measures whether the household has taken any loan for education expenditure in a given year. The other dependent variable in Column 2, education loan amount, measures the amount of loans taken for education in a given year, in terms of real values. A Tobit model is used to estimate the effect of FGGS on loan amounts in Column 2. Also, Panel A includes all educational loans taken by the household, Panel B includes education loans taken only through institutional credit agencies, and Panel C includes education loans taken only through non-institutional credit agencies. Data is sourced from the NSS 70th round (year 2013). The sample consists of first-generation households (households with eligible individuals aged 17–25 and attending college) in Tamil Nadu, Kerala, and Karnataka. Control variables include social group, religion, household size, and rural residence. DiD estimates are controlled for district and year fixed effects, while the Tobit model (left-censored at zero) is controlled for year fixed effects and includes district-level means of all time-varying covariates (Mundlak adjustment) in lieu of district fixed effects. Robust standard errors, clustered at the district level, are reported in parentheses. The symbols ***, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Expenditure on technical degree education

	Expenditure on Education (1)	Share of Expenditure on Education (2)	Course Fee (3)	Share of Course Fee (4)
TN × Post	-18286	-9.970**	-17296	-10.310**
	(14454)	(4.241)	(11254)	(3.993)
Controls	Yes	Yes	Yes	Yes
District FE	No	No	No	No
Year FE	No	No	No	No
Mean Dep Variable	66206	32.585	48150	23.514
Observations	643	643	640	640

Notes: The dependent variables include educational expenditure (real), course fees (real), the share of educational expenditure as a fraction of the household's total annual expenditure, and the share of course fees as a fraction of the household's total annual expenditure. A household's total annual expenditure is estimated by multiplying its usual monthly consumption expenditure by 12 and adding the household's annual expenditure on education. Data is sourced from NSS rounds 64 and 71 for the years 2007 and 2014, respectively. The sample consists of 17–22-year-old first-generation students enrolled in technical graduate courses in Tamil Nadu, Kerala, and Karnataka. Each regression includes control variables such as sex, age, marital status, caste and religion, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. The model also accounts for year and district-fixed effects. Robust standard errors, clustered at the district level, are reported in parentheses, and observations are weighted using NSS sampling weights. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

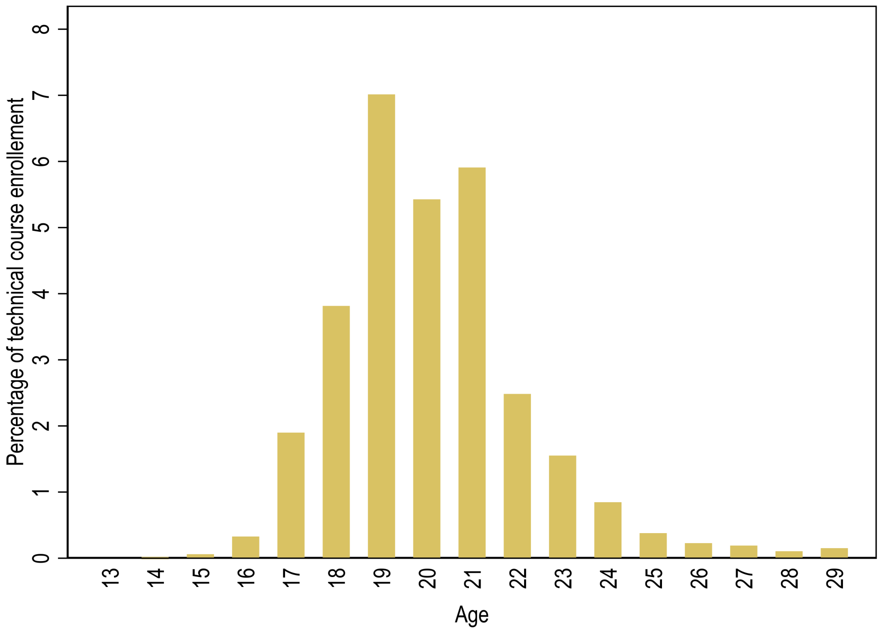
Table 7: Effect of FGGS scheme on social welfare

	MPCE		MPCE (log)	
	DID	Synthetic DID	DID	Synthetic DID
	(1)	(2)	(3)	(4)
TN × Post	491.538***	573.642***	0.328***	0.359***
	(62.413)	(122.717)	(0.041)	(0.072)
Controls	Yes	Yes	Yes	Yes
District FE	Yes	-	Yes	-
Year FE	Yes	-	Yes	-
Mean Dep Variable	1542.405	1331.954	7.195	7.151
Observations	15596	90	15596	90
Pre-trends test p-value	0.955	-	0.447	-

Notes: The dependent variable is monthly per capita expenditure (MPCE) in real value (2011) in columns 1-2 and in log transformed value in columns 3-4. Data are sourced from NSS and PLFS rounds for the years 2007, 2009, 2011, 2017, and 2018. The sample is defined as first-generation households of Tamil Nadu, Kerala, and Karnataka with 25-29-year-old individuals. Control variables such as the proportion of females and maximum age of the household in the age group of 25-29, caste and religion, the highest education level of a family member, and household size. Columns (2) and (4) report results from the Synthetic DiD method, where state-level panel data are created by aggregating individual-level data over six years across 18 states. Standard errors are clustered at the district level for DiD estimates. For Synthetic DiD estimates, placebo-method standard errors are used. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

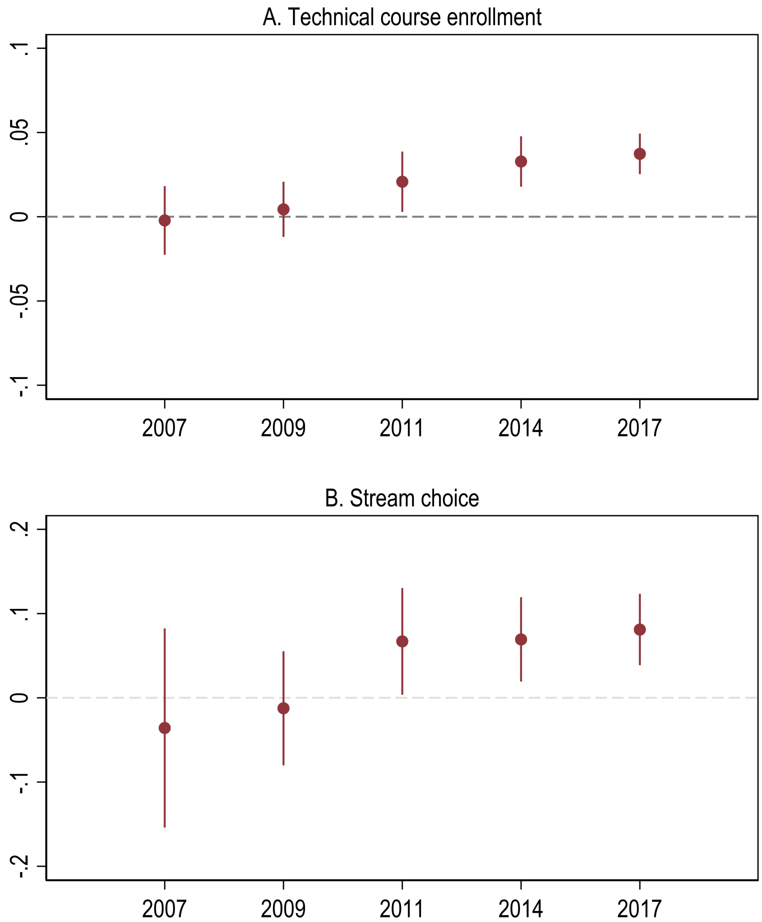
Supplementary Appendix

Figure A.1: Age distribution of undergraduate students attending technical courses in India



Notes: This figure shows the histogram of age-wise technical course current undergraduate enrollment in India. Data are sourced from NSS rounds for the years 2007, 2009, 2011, 2017, and 2018.

Figure A.2: Placebo test for technical course enrolment



Notes: Each point on the horizontal axis represents the estimated difference-in-differences (DiD) coefficient from a separate regression, corresponding to a specific placebo iteration. Round markers indicate the estimate using samples restricted to the years up to a specific year marked on the horizontal axis. Before the actual treatment period (2010), the last year in each placebo iteration serves as the pseudo-post-treatment year. For instance, the coefficient for 2009 is derived from a DiD regression using data from 2004 to 2009, treating 2009 as the pseudo-implementation year. After the actual treatment period (2010), all subsequent years (2011 and beyond) are treated as post-treatment in the respective iterations. Vertical lines represent 95% confidence intervals. Data is sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. Each regression includes control variables such as sex, age, marital status, caste and religion, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. The model accounts for year and district fixed effects, with standard errors clustered at the district level. Observations are weighted using NSS sampling weights.

Table A.1: Variable Descriptions

Variable	**Description**
	Educational Outcomes
Technical course enrollment	Dummy = 1 if enrolled in an undergraduate program in engineering, medicine, or agriculture; 0 otherwise.
Stream choice	Dummy = 1 if enrolled in an undergraduate program in engineering, medicine, or agriculture; 0 if enrolled in other undergraduate (non-professional) courses.
	Labour Market Outcomes
	Educational attainment
Technical graduation	Dummy = 1 if completed an undergraduate program in engineering, medicine, or agriculture; 0 otherwise.
Stream choice	Dummy = 1 if completed an undergraduate program in engineering, medicine, or agriculture; 0 if completed other undergraduate (non-professional) courses.
	Employment type
Self-employed	Dummy = 1 if individual is working in a household enterprise as own-account worker, employer, or unpaid family worker; 0 otherwise.
Regular employee	Dummy = 1 if individual is in regular salaried/wage employment; 0 otherwise.
Casual labour	Dummy = 1 if individual is in a casual job in public works or other sectors; 0 otherwise.
Available for work	Dummy = 1 if individual is seeking/available for work but not employed; 0 otherwise.
Not in labour force	Dummy = 1 if engaged in non-economic activities or unable to work; 0 otherwise.
	Industry type
Agriculture Sector	Dummy = 1 if individual is employed in the agriculture sector; 0 if individual is employed in other sectors.
Secondary Sector	Dummy = 1 if individual is employed in secondary (manufacturing) sector; 0 if individual is employed in other sectors.
Service Sector	Dummy = 1 if individual is employed in the service sector; 0 if individual is employed in other sectors.

Continued on next page

Table A.1 – continued from previous page

Variable	Description
	Occupation type
Professionals	Dummy = 1 if an individual is employed in advanced problem-solving, decision-making, and creative tasks 1; 0 if an individual is employed in other kinds of tasks.
Associate Professionals	Dummy = 1 if an individual is employed in complex technical tasks requiring specialised knowledge 1 ; 0 if an individual is employed in other kinds of tasks.
Secondary Occupations	Dummy = 1 if an individual is employed in operating machinery and maintenance work 1; 0 if an individual is employed in other kinds of tasks.
Elementary occupations	Dummy = 1 if an individual is employed in simple and routine physical or manual tasks 1; 0 if an individual is employed in other kinds of tasks.
Others	Dummy = 1 if an individual is employed in an occupation type that is undefined (Legislators, Senior Officials, Managers); 0 if an individual is employed in other kinds of tasks.
	Other Outcome variables
Education expenditure	Total real expenditure on education (real value), including course fees and other expenses, for individuals enrolled in professional courses.
Course fee share	Course fee as a share of the household's total annual expenditure.
Education expenditure share	Education expenditure as a fraction of the household's total annual expenditure.
Education loan	Dummy = 1 if the household borrowed for education in a given year; 0 otherwise.
Education loan amount	Total annual amount borrowed by the household for education (real value) in a given year.
MPCE (Real)	Monthly per capita expenditure in real terms.
MPCE (Log)	Logarithm of the real value of monthly per capita expenditure.

Table A.2: Details of scholarship amount sanctioned and benefitted students

Academic Year	Amount Sanctioned (Rs. in crore)	Number of Students Benefitted	Total UG Enrollment (Regular Mode) in the State	Percentage of Beneficiaries
2011-12	299.28	157,176	1,721,746	9.13
2012-13	478.06	249,563	1,850,369	13.49
2013-14	547.87	287,021	1,937,723	14.81
2014-15	541.11	283,379	2,030,479	13.96
2015-16	514.53	269,522	2,044,777	13.18
2016-17	459.03	242,112	2,138,408	11.32
2017-18	434.56	217,396	2,250,057	9.66
2018-19	402.94	191,268	2,264,580	8.45

Notes: Data on scholarship amount and beneficiaries are sourced from the higher education department policy note submitted in the Tamil Nadu assembly (See: https://cms.tn.gov.in/cms_migrated/document/docfiles/hedu_e_pn_2016_17.pdf). Data on total UG Enrollment derived from the All India Survey on Higher Education (AISHE) published by the Ministry of Education for the respective years.

Table A.3: Summary statistics for labour market outcomes

	Full Sample				Graduated Sample			
	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Individual level variables								
Technical graduates	0.03	0.16	0	1	0.13	0.34	0	1
Employment type								
Regular employee	0.20	0.40	0	1	0.41	0.49	0	1
Self-employed	0.18	0.38	0	1	0.10	0.30	0	1
Casual labour	0.18	0.38	0	1	0.02	0.15	0	1
Available for work	0.08	0.28	0	1	0.22	0.41	0	1
Not in labour force	0.38	0.48	0	1	0.28	0.45	0	1
Others	0.07	0.25	0	1	0.07	0.26	0	1
Industry type								
Agriculture sector	0.15	0.35	0	1	0.04	0.19	0	1
Secondary sector	0.19	0.39	0	1	0.08	0.28	0	1
Service sector	0.23	0.42	0	1	0.41	0.49	0	1
Occupation type								
Professionals	0.03	0.18	0	1	0.12	0.32	0	1
Associate professionals	0.04	0.19	0	1	0.11	0.32	0	1
Secondary occupations	0.30	0.46	0	1	0.20	0.40	0	1
Elementary occupations	0.14	0.34	0	1	0.02	0.15	0	1
Female	0.55	0.50	0	1	0.50	0.50	0	1
Age 25 years	0.23	0.42	0	1	0.25	0.43	0	1
Age 26 years	0.21	0.40	0	1	0.23	0.42	0	1
Age 27 years	0.18	0.38	0	1	0.19	0.39	0	1
Age 28 years	0.25	0.43	0	1	0.19	0.40	0	1
Age 29 years	0.14	0.35	0	1	0.13	0.34	0	1
Relation to household head								
Household head	0.04	0.19	0	1	0.02	0.15	0	1
Unmarried child	0.32	0.47	0	1	0.49	0.50	0	1
Other relations	0.65	0.48	0	1	0.49	0.50	0	1
Ever married	0.65	0.48	0	1	0.46	0.50	0	1
Household level variables								
Household size	4.82	1.99	2	35	4.38	1.53	2	35
Social category								
Scheduled Caste	0.04	0.19	0	1	0.01	0.11	0	1
Scheduled Tribe	0.21	0.41	0	1	0.17	0.37	0	1
Other Backward Class	0.62	0.48	0	1	0.65	0.48	0	1
Other social group	0.13	0.34	0	1	0.17	0.38	0	1
Religion								
Hindu	0.82	0.38	0	1	0.84	0.37	0	1
Muslim	0.12	0.33	0	1	0.08	0.26	0	1
Other religions	0.06	0.23	0	1	0.09	0.28	0	1
Highest education of the household								
Illiterate	0.21	0.40	0	1	0.10	0.31	0	1
Primary and below	0.23	0.42	0	1	0.17	0.37	0	1
Upper primary and secondary	0.43	0.49	0	1	0.48	0.50	0	1
Above secondary	0.13	0.34	0	1	0.25	0.43	0	1
Urban	0.37	0.48	0	1	0.53	0.50	0	1
Other variables								
No. of colleges	71.94	101.40	1	460	85.88	112.07	1	460
Proportion of technical colleges	0.54	0.14	0	1	0.57	0.13	0	1
TN	0.42	0.49	0	1	0.52	0.50	0	1
Post	0.83	0.38	0	1	0.91	0.28	0	1
Observations	18397				3035			

Notes: Data was sourced from NSS and PLFS rounds for the years 2009, 2011, 2017, and 2018. The full sample is defined as 15-29-year-old individuals from first-generation households in three states: Tamil Nadu, Kerala, and Karnataka. The sample is further restricted to those individuals who have graduated in any course (Graduated).

Table A.4: Event study analysis for the effects on technical course enrollment

	Technical Course Enrollment (1)	Stream Choice (2)
TN × 2004	-0.002	0.052
	(0.011)	(0.054)
TN × 2007	0.001	0.041
	(0.009)	(0.035)
TN × 2011	0.020*	0.089**
	(0.011)	(0.036)
TN × 2014	0.045***	0.097**
	(0.013)	(0.037)
TN × 2017	0.050***	0.129***
	(0.010)	(0.034)
Controls	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Mean Dep Variable	0.031	0.143
Observations	35184	11699

Notes: The dependent variable indicates whether an individual has enrolled in a graduate degree program in engineering, medicine, or agriculture. Data is sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The sample consists of individuals aged 17–22 from first-generation households in Tamil Nadu, Kerala, and Karnataka in column (1). And it is further restricted to individuals currently enrolled in any graduate course in column (2). Table presents coefficients from a regression using an event study specification (Year 2009 serves as the omitted category. Control variables such as sex, age, marital status, caste, religion, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. Robust standard errors, clustered at the district level, are reported in parentheses, and observations are weighted using NSS sampling weights. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.5: Robustness check: Border districts sample

	Technical Course Enrollment			Stream Choice		
	(1)	(2)	(3)	(4)	(5)	(6)
TN × Post	0.038***	0.037***	0.037***	0.084***	0.079***	0.081***
	(0.006)	(0.006)	(0.006)	(0.021)	(0.022)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No
District FE	No	No	Yes	No	No	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Mean Dep Variable	0.031	0.031	0.031	0.143	0.143	0.143
Observations	35184	35184	35184	11699	11699	11699

Notes: The dependent variable indicates whether an individual has enrolled in a graduate degree program in engineering, medicine, or agriculture. Data is sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The sample consists of individuals aged 17–22 from first-generation households in Tamil Nadu, Kerala, and Karnataka in columns (1)–(3). And it is further restricted to individuals currently enrolled in any graduate course in columns (4)–(6). Additionally, all samples are limited to the border districts of Tamil Nadu and districts in Kerala and Karnataka that share a border with Tamil Nadu. Control variables such as sex, age, marital status, caste, religion, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. Robust standard errors, clustered at the district level, are reported in parentheses, and observations are weighted using NSS sampling weights. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.6: Heterogeneity by gender

	Technical Course Enrollment (1)	Stream Choice (2)
TN × Post	0.060***	0.152***
	(0.009)	(0.031)
TN × Post × Female	-0.046***	-0.157***
	(0.011)	(0.041)
Marginal Effects		
Male	0.060***	0.152***
	(0.009)	(0.031)
Female	0.014*	-0.005
	(0.007)	(0.027)
Controls	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Mean Dep Variable	0.031	0.143
Observations	35184	11699

Notes: The table illustrates the heterogeneous impact of FGGS on the educational outcomes of first-generation students by gender. The dependent variable indicates whether an individual has enrolled in a graduate degree program in engineering, medicine, or agriculture. Data is sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The sample consists of individuals aged 17–22 from first-generation households in Tamil Nadu, Kerala, and Karnataka in column (1). And it is further restricted to individuals currently enrolled in any graduate course in column (2). Control variables such as age, marital status, caste, religion, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. Robust standard errors, clustered at the district level, are reported in parentheses, and observations are weighted using NSS sampling weights. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.7: Heterogeneity by religion

	Technical Course Enrollment (1)	Stream Choice (2)
TN × Post	0.042***	0.107***
	(0.007)	(0.024)
TN × Post × Muslim	-0.013	0.005
	(0.028)	(0.109)
TN × Post × Others	-0.031	-0.117*
	(0.024)	(0.066)
Marginal Effects		
Hindu	0.042***	0.107***
	(0.007)	(0.024)
Muslim	0.029	0.112
	(0.027)	(0.106)
Others	0.011	-0.010
	(0.022)	(0.059)
Controls	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Mean Dep Variable	0.031	0.143
Observations	35180	11690

Notes: The table illustrates the heterogeneous impact of FGGS on the educational outcomes of first-generation students by religion. The dependent variable indicates whether an individual has enrolled in a graduate degree program in engineering, medicine, or agriculture. Data is sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The sample consists of individuals aged 17–22 from first-generation households in Tamil Nadu, Kerala, and Karnataka in column (1). And it is further restricted to individuals currently enrolled in any graduate course in column (2). Each regression includes control variables such as sex, age, marital status, caste, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. The model also accounts for year and district fixed effects. Robust standard errors, clustered at the district level, are reported in parentheses, and observations are weighted using NSS sampling weights. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.8: Heterogeneity by social group

	Technical Course Enrollment (1)	Stream Choice (2)
TN × Post	0.044	0.113
	(0.033)	(0.126)
N × Post × ST	0.035	0.422**
	(0.067)	(0.173)
TN × Post × SC	-0.028	-0.079
	(0.032)	(0.128)
TN × Post × OBC	0.007	-0.001
	(0.032)	(0.130)
Marginal Effects		
ST	0.079	0.535***
	(0.059)	(0.140)
SC	0.017*	0.034
	(0.010)	(0.059)
OBC	0.051***	0.112***
	(0.007)	(0.028)
Others	0.044	0.113
	(0.033)	(0.126)
Controls	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Mean Dep Variable	0.031	0.143
Observations	35179	11682

Notes: The table illustrates the heterogeneous impact of FGGS on the educational outcomes of first-generation students by social group. The dependent variable indicates whether an individual has enrolled in a graduate degree program in engineering, medicine, or agriculture. Data is sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The sample consists of individuals aged 17–22 from first-generation households in Tamil Nadu, Kerala, and Karnataka in column (1). And it is further restricted to individuals currently enrolled in any graduate course in column (2). Each regression includes control variables such as sex, age, marital status, religion, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. The model also accounts for year and district fixed effects. Robust standard errors, clustered at the district level, are reported in parentheses, and observations are weighted using NSS sampling weights. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.9: Heterogeneity by household education level

	Technical Course Enrollment (1)	Stream Choice (2)
TN × Post	0.031***	0.094
	(0.008)	(0.059)
TN × Post × Primary & below	0.005	-0.003
	(0.010)	(0.064)
TN × Post × Upper primary & secondary	0.021	0.042
	(0.013)	(0.066)
TN × Post × Above secondary	-0.045	-0.162**
	(0.031)	(0.081)
Marginal Effects		
Illiterate	0.031***	0.094
	(0.008)	(0.059)
Primary & below	0.036***	0.090*
	(0.008)	(0.048)
Upper primary & secondary	0.052***	0.135***
	(0.010)	(0.029)
Above secondary	-0.014	-0.069
	(0.028)	(0.053)
Controls	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Mean Dep Variable	0.031	0.143
Observations	35184	11693

Notes: The table illustrates the heterogeneous impact of FGGS on the educational outcomes of first-generation students by the highest education level of a family member. The dependent variable indicates whether an individual has enrolled in a graduate degree program in engineering, medicine, or agriculture. Data is sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The sample consists of individuals aged 17–22 from first-generation households in Tamil Nadu, Kerala, and Karnataka in column (1). And it is further restricted to individuals currently enrolled in any graduate course in column (2). Each regression includes control variables such as sex, age, marital status, caste, religion, household size, number of colleges in the district, and the proportion of technical colleges in the district. The model also accounts for year and district fixed effects. Robust standard errors, clustered at the district level, are reported in parentheses, and observations are weighted using NSS sampling weights. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.10: Heterogeneity by sector

	Technical Course Enrollment (1)	Stream Choice (2)
TN × Post	0.052***	0.088***
	(0.010)	(0.024)
TN × Post × Rural	-0.024**	-0.004
	(0.012)	(0.041)
Marginal Effects		
Rural	0.028***	0.084**
	(0.008)	(0.035)
Urban	0.052***	0.088***
	(0.010)	(0.024)
Controls	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Mean Dep Variable	0.031	0.143
Observations	35184	11699

Notes: The table illustrates the heterogeneous impact of FGGS on the educational outcomes of first-generation students by sector. The dependent variable indicates whether an individual has enrolled in a graduate degree program in engineering, medicine, or agriculture. Data is sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The sample consists of individuals aged 17–22 from first-generation households in Tamil Nadu, Kerala, and Karnataka in column (1). And it is further restricted to individuals currently enrolled in any graduate course in column (2). Each regression includes control variables such as sex, age, marital status, caste, religion, highest education level of a family member, household size, number of colleges in the district, and the proportion of technical colleges in the district. The model also accounts for year and district fixed effects. Robust standard errors, clustered at the district level, are reported in parentheses, and observations are weighted using NSS sampling weights. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.11: Effect of FGGS scheme on technical course enrolment (Subsample by sex)

	Technical Course Enrollment				Stream Choice			
	DID			Synthetic DID	DID			Synthetic DID
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Male								
TN × Post	0.060***	0.060***	0.060***	0.059***	0.154***	0.148***	0.152***	0.096**
	(0.010)	(0.010)	(0.009)	(0.013)	(0.032)	(0.033)	(0.031)	(0.046)
Mean Dep Variable	0.039	0.039	0.039	0.021	0.165	0.165	0.165	0.111
Observations	18498	18498	18498	108	6884	6884	6884	108
Pre-trends test p-value	0.858	0.974	0.892	-	0.201	0.477	0.461	-
Panel B - Female								
TN × Post	0.015*	0.014*	0.014*	0.016	-0.003	-0.005	-0.005	0.062
	(0.007)	(0.007)	(0.007)	(0.014)	(0.029)	(0.029)	(0.027)	(0.045)
Mean Dep Variable	0.023	0.023	0.023	0.012	0.116	0.116	0.116	0.091
Observations	16686	16686	16686	108	4815	4815	4815	108
Pre-trends test p-value	0.393	0.987	0.955		0.310	0.765	0.764	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	-	No	Yes	No	-
District FE	No	No	Yes	-	No	No	Yes	-
Year FE	No	Yes	Yes	-	No	Yes	Yes	-

Notes: The dependent variable indicates whether an individual has enrolled in a graduate degree program in engineering, medicine, or agriculture (Technical Course Enrollment) or chosen a technical stream while enrolled in an undergraduate course (Stream Choice). Data are sourced from NSS rounds for the years 2004, 2007, 2009, 2011, 2014, and 2017. The sample consists of individuals aged 17–22 from first-generation households in Tamil Nadu, Kerala, and Karnataka in columns (1)–(4). And it is further restricted to individuals currently enrolled in a graduate course in columns (5)–(8). Also, Panel A restricts the sample to males, while Panel B focuses on females. Control variables include sex, age, marital status, caste, religion, the highest education level of a family member, household size, the number of colleges in the district, and the proportion of technical colleges in the district. Columns (4) and (8) report results from the Synthetic DiD method, where state-level panel data are created by aggregating individual-level data over six years across 18 states. For Synthetic DiD estimates, placebo-method standard errors are used. Observations are weighted using NSS sampling weights. Observations are weighted using NSS sampling weights. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.12: Effect of FGGS scheme on educational attainment and employment type (Subsample by sex)

	Educational Attainment		Employment Type				
	Technical Graduation (1)	Stream Choice (2)	Self Employed (3)	Regular Employee (4)	Casual Labour (5)	Available for Work (6)	Not in Labour Force (7)
Panel A1 - Male (DiD Model)							
TN × Post	0.053***	0.122**	0.007	0.039	-0.041	0.064***	-0.023*
	(0.013)	(0.046)	(0.035)	(0.037)	(0.039)	(0.019)	(0.013)
Mean Dep Variable	0.044	0.203	0.282	0.329	0.276	0.105	0.033
Observations	6608	1305	8394	8394	8394	8394	8394
Pre-trends test p-value	0.320	0.066	0.829	0.417	0.587	0.703	0.611
Panel A2 - Male (Synthetic DiD Model)							
TN × Post	0.069***	0.220***	-0.038	0.163**	-0.130*	0.048	-0.029
	(0.013)	(0.077)	(0.098)	(0.063)	(0.066)	(0.035)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.013	0.070	0.435	0.252	0.308	0.055	0.040
Observations	72	72	90	90	90	90	90
Panel B1 - Female (DiD Model)							
TN × Post	0.022***	0.060**	0.032	0.041**	-0.038	0.029	-0.039
	(0.006)	(0.029)	(0.027)	(0.019)	(0.026)	(0.021)	(0.043)
Mean Dep Variable	0.013	0.070	0.097	0.103	0.103	0.065	0.660
Observations	7767	1367	10003	10003	10003	10003	10003
Pre-trends test p-value	0.318	0.353	0.910	0.941	0.474	0.694	0.538
Panel B2 - Female (Synthetic DiD Model)							
TN × Post	0.024***	0.088*	0.028	0.065	-0.025	0.001	-0.018
	(0.008)	(0.046)	(0.042)	(0.070)	(0.069)	(0.037)	(0.050)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.004	0.028	0.197	0.052	0.099	0.031	0.730
Observations	72	72	90	90	90	90	90

Notes: The dependent variables for educational attainment indicate whether an individual has completed graduation in a technical course such as engineering, medicine, or agriculture (Technical graduation) and chosen a technical stream conditional on graduation (Stream Choice). The dependent variables for type of employment are binary variables derived from the individual's activity status. Data are sourced from NSS and PLFS rounds for the years 2007 (not for first-order outcomes), 2009, 2011, 2017, and 2018. The sample consists of individuals aged 25–29 from first-generation households in Tamil Nadu, Kerala, and Karnataka. And it is further restricted to those individuals who have completed graduation in any course in (2). Also, Panels A1 and A2 restrict the sample to males, while Panels B1 and B2 focus on females. Control variables such as sex, age, marital status, caste, religion, the highest education level of a family member, household size, the number of colleges in the district, and the proportion of technical colleges in the district. The model also accounts for year and district fixed effects. Panels A2 and B2 report results from the Synthetic DiD method, where state-level panel data are created by aggregating individual-level data over six years across 18 states. For Synthetic DiD estimates, placebo-method standard errors are used. Observations are weighted using NSS sampling weights. Observations are weighted using NSS sampling weights. The symbols ***, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.13: Effect of FGGS scheme on industry type and occupation type (Subsample by sex)

	Industry Type			Occupation Type				
	Agriculture Sector (1)	Secondary Sector (2)	Service Sector (3)	Professionals (4)	Associate Professionals (5)	Secondary Occupations (6)	Elementary Occupations (7)	Others (8)
Panel A1 - Male (DiD Model)								
TN × Post	-0.038	-0.009	0.066*	0.025*	0.029*	0.099**	-0.034	-0.085***
	(0.037)	(0.035)	(0.037)	(0.015)	(0.015)	(0.043)	(0.038)	(0.022)
Mean Dep Variable	0.223	0.345	0.454	0.046	0.056	0.582	0.206	0.133
Observations	7564	7564	7564	7564	7564	7564	7564	7564
Pre-trends test p-value	0.991	0.413	0.810	0.128	0.818	0.063	0.833	0.026
Panel A2 - Male (Synthetic DiD Model)								
TN × Post	0.011	-0.096	0.157**	0.023	0.107***	0.091	-0.120	-0.020
	(0.074)	(0.116)	(0.065)	(0.014)	(0.036)	(0.113)	(0.107)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.399	0.342	0.357	0.042	0.038	0.642	0.291	0.063
Observations	90	90	90	90	90	90	90	90
Panel B1 - Female (DiD Model)								
TN × Post	-0.097	0.092	0.010	-0.017	0.047*	0.027	-0.016	-0.013
	(0.066)	(0.063)	(0.042)	(0.034)	(0.027)	(0.078)	(0.065)	(0.031)
Mean Dep Variable	0.369	0.315	0.353	0.091	0.089	0.425	0.342	0.080
Observations	2966	2966	2966	2966	2966	2966	2966	2966
Pre-trends test p-value	0.146	0.438	0.033	0.553	0.239	0.553	0.904	0.026
Panel B2 - Female (Synthetic DiD Model)								
TN × Post	-0.112	0.110	-0.008	-0.014	0.012	-0.009	0.068	-0.005
	(0.132)	(0.118)	(0.092)	(0.074)	(0.058)	(0.178)	(0.194)	(0.096)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.597	0.209	0.244	0.055	0.058	0.587	0.313	0.041
Observations	90	90	90	90	90	90	90	90

Notes: The dependent variables are binary indicators representing the type of industry in which an individual is employed and the occupation type of the employment. Data are sourced from NSS and PLFS rounds for the years 2007, 2009, 2011, 2017, and 2018. The sample consists of employed individuals aged 25–29 from first-generation households in Tamil Nadu, Kerala, and Karnataka. Also, Panels A1 and A2 restrict the sample to males, while Panels B1 and B2 focus on females. Control variables include sex, age, marital status, caste, religion, the highest education level of a family member, household size, the number of colleges in the district, and the proportion of technical colleges in the district. The model also accounts for year and district fixed effects. Panels A2 and B2 report results from the Synthetic DiD method, where state-level panel data are created by aggregating individual-level data over six years across 18 states. For Synthetic DiD estimates, placebo-method standard errors are used. Observations are weighted using NSS sampling weights. Observations are weighted using NSS sampling weights. The symbols ***, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.14: Effect of FGGS scheme on educational attainment and employment type (sample size is restricted to two pre-treatment year data)

	Educational Attainment		Employment Type				
	Technical Graduation (1)	Stream Choice (2)	Self Employed (3)	Regular Employee (4)	Casual Labour (5)	Available for Work (6)	Not in Labour Force (7)
Panel A - (DiD Model)							
TN × Post	0.036***	0.094***	0.013	0.038	-0.046*	0.051***	-0.040
	(0.006)	(0.026)	(0.024)	(0.023)	(0.025)	(0.014)	(0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.027	0.136	0.175	0.210	0.174	0.086	0.379
Observations	14375	2674	14375	14375	14375	14375	14375
Pre-trends test p-value	0.064	0.046	0.932	0.357	0.633	0.312	0.449
Panel B - (Synthetic DiD Model)							
TN × Post	0.048***	0.150***	0.022	0.137**	-0.096*	0.018	-0.030
	(0.009)	(0.055)	(0.102)	(0.061)	(0.053)	(0.024)	(0.054)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.009	0.053	0.303	0.162	0.196	0.047	0.381
Observations	72	72	72	72	72	72	72

Notes: This table reports the coefficients from the DiD and Synthetic DiD specifications similar to table 3, but pre-treatment year data is only restricted to two years (2009 and 2011). The dependent variables for educational attainment indicate whether an individual has completed graduation in a technical course such as engineering, medicine, or agriculture (Technical graduation) and chosen a technical stream conditional on graduation (Stream Choice). The dependent variables for type of employment are binary variables derived from the individual's activity status. Data are sourced from NSS and PLFS rounds for the years 2009, 2011, 2017, and 2018. The sample consists of individuals aged 25–29 from first-generation households in Tamil Nadu, Kerala, and Karnataka (Column 1). And it is further restricted to those individuals who have completed graduation in any course in column 2. Control variables include sex, age, marital status, caste, religion, the highest education level of a family member, household size, the number of colleges in the district, and the proportion of technical colleges in the district. Panel B reports results from the Synthetic DiD method, where state-level panel data are created by aggregating individual-level data over six years across 18 states. For Synthetic DiD estimates, placebo-method standard errors are used. Observations are weighted using NSS sampling weights. Observations are weighted using NSS sampling weights. The symbols ***, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.15: Effect of FGGS scheme on industry type and occupation type (sample size is restricted to two pre-treatment year data)

	Industry Type			Occupation Type				
	Agriculture Sector (1)	Secondary Sector (2)	Service Sector (3)	Professionals (4)	Associate Professionals (5)	Secondary Occupations (6)	Elementary Occupations (7)	Others (8)
Panel A - (DiD Model)								
TN × Post	-0.056	-0.003	0.062*	0.011	0.036**	0.035	-0.034	-0.045**
	(0.038)	(0.034)	(0.031)	(0.016)	(0.016)	(0.040)	(0.037)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.251	0.340	0.435	0.061	0.068	0.532	0.237	0.122
Observations	8090	8090	8090	8090	8090	8090	8090	8090
Pre-trends test p-value	0.253	0.720	0.142	0.628	0.444	0.802	0.871	0.406
Panel B - (Synthetic DiD Model)								
TN × Post	0.015	-0.126	0.143**	0.034	0.100***	0.041	-0.099	-0.028
	(0.069)	(0.090)	(0.059)	(0.021)	(0.031)	(0.130)	(0.110)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.428	0.323	0.334	0.044	0.041	0.634	0.284	0.060
Observations	72	72	72	72	72	72	72	72

Notes: This table reports the coefficients from the DiD and Synthetic DiD specifications similar to Table 4, but pre-treatment year data is only restricted to two years (2009 and 2011). The dependent variables are binary indicators representing the type of industry in which an individual is employed and the occupation type of the employment. Data are sourced from NSS and PLFS rounds for the year 2009, 2011, 2017, and 2018. The sample consists of employed individuals aged 25–29 from first-generation households in Tamil Nadu, Kerala, and Karnataka. Control variables include sex, age, marital status, caste, religion, the highest education level of a family member, household size, the number of colleges in the district, and the proportion of technical colleges in the district. Panel B reports results from the Synthetic DiD method, where state-level panel data are created by aggregating individual-level data over six years across 18 states. For Synthetic DiD estimates, placebo-method standard errors are used. Observations are weighted using NSS sampling weights. Observations are weighted using NSS sampling weights. The symbols ***, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.16: Effect of FGGS scheme on technical course enrolment (Complete estimates)

	Technical Course Enrollment			Stream Choice		
	(1)	(2)	(3)	(4)	(5)	(6)
TN × Post	0.038***	0.037***	0.037***	0.084***	0.079***	0.081***
	(0.006)	(0.006)	(0.006)	(0.021)	(0.022)	(0.021)
Post=1	0.009***			0.026**		
	(0.003)			(0.012)		
TN=1	0.007**			0.046***		
	(0.003)			(0.016)		
Female	-0.012***	-0.012***	-0.012***	-0.053***	-0.058***	-0.059***
	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)	(0.011)
Age 18 years	0.020***	0.021***	0.021***	0.005	0.008	0.007
	(0.003)	(0.003)	(0.003)	(0.016)	(0.016)	(0.016)
Age 19 years	0.030***	0.031***	0.031***	0.017	0.018	0.019
	(0.005)	(0.005)	(0.005)	(0.016)	(0.016)	(0.016)
Age 20 years	0.019***	0.020***	0.020***	0.035**	0.037**	0.036**
	(0.004)	(0.004)	(0.004)	(0.017)	(0.016)	(0.017)
Age 21 years	0.011**	0.011**	0.012**	0.106***	0.103***	0.104***
	(0.005)	(0.005)	(0.005)	(0.025)	(0.024)	(0.024)
Age 22 years	-0.003	-0.002	-0.003	0.057**	0.056**	0.054*
	(0.004)	(0.004)	(0.004)	(0.027)	(0.027)	(0.028)
Unmarried Child	0.026***	0.022***	0.020***	-0.109	-0.086	-0.081
	(0.006)	(0.008)	(0.007)	(0.232)	(0.246)	(0.256)
Other relations	0.007	0.003	0.001	-0.118	-0.093	-0.086
	(0.007)	(0.008)	(0.008)	(0.237)	(0.252)	(0.262)
Scheduled Tribe	-0.014***	-0.013***	-0.013***	-0.063**	-0.056**	-0.050*
	(0.004)	(0.004)	(0.005)	(0.024)	(0.025)	(0.025)
Scheduled Caste	-0.016***	-0.017***	-0.017***	-0.049***	-0.047***	-0.052***
	(0.005)	(0.005)	(0.005)	(0.018)	(0.018)	(0.018)
Other Backward Class	-0.001	-0.002	-0.003	-0.004	-0.002	-0.009
	(0.003)	(0.003)	(0.004)	(0.012)	(0.012)	(0.012)
Muslim	-0.012***	-0.015***	-0.013***	-0.030	-0.033*	-0.025
	(0.004)	(0.004)	(0.004)	(0.018)	(0.019)	(0.020)
Other religions	0.016*	0.011	0.005	0.009	-0.000	-0.006
	(0.008)	(0.008)	(0.008)	(0.020)	(0.020)	(0.021)
Primary & below	0.005*	0.004	0.004	0.017	0.014	0.019
	(0.003)	(0.003)	(0.003)	(0.018)	(0.019)	(0.020)
Upper primary & secondary	0.025***	0.022***	0.023***	0.052***	0.049***	0.053***
	(0.004)	(0.004)	(0.004)	(0.017)	(0.018)	(0.018)
Above secondary	0.059***	0.056***	0.056***	0.103***	0.098***	0.101***
	(0.006)	(0.006)	(0.006)	(0.019)	(0.020)	(0.020)
Household Size	-0.002***	-0.002***	-0.002***	-0.007**	-0.007**	-0.007**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
No. of Colleges	-0.000	0.000	0.000**	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Proportion of Technical Colleges	0.022**	0.017*	0.045**	0.137***	0.115***	0.318***
	(0.009)	(0.009)	(0.020)	(0.040)	(0.041)	(0.116)
Urban	0.014***	0.014***	0.014***	0.033***	0.030***	0.030**
	(0.003)	(0.003)	(0.004)	(0.011)	(0.011)	(0.013)
Constant	-0.031***	-0.016*	-0.040**	0.095	0.122	0.013
	(0.007)	(0.008)	(0.016)	(0.233)	(0.248)	(0.268)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No
District FE	No	No	Yes	No	No	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Mean Dep Variable	0.031	0.031	0.031	0.143	0.143	0.143
Observations	35184	35184	35184	11699	11699	11699

Notes: This is the detailed version of Table 2. Robust standard errors are clustered at the district level in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.17: Effect of FGGS scheme on employment type (Complete estimates)

	Self Employed (1)	Regular Employee (2)	Casual Labour (3)	Available for Work (4)	Not in Labour Force (5)
TN × Post	0.015	0.043*	-0.038	0.050***	-0.036
	(0.023)	(0.023)	(0.024)	(0.013)	(0.027)
Female	-0.218***	-0.164***	-0.169***	0.013	0.544***
	(0.017)	(0.014)	(0.017)	(0.015)	(0.017)
Age 26 years	0.028*	0.034*	-0.013	-0.019	-0.024
	(0.015)	(0.018)	(0.019)	(0.013)	(0.015)
Age 27 years	0.037**	0.045***	0.008	-0.030**	-0.047***
	(0.016)	(0.016)	(0.017)	(0.014)	(0.015)
Age 28 years	0.033**	0.029**	0.033*	-0.027**	-0.047***
	(0.016)	(0.013)	(0.018)	(0.011)	(0.016)
Age 29 years	0.070***	0.011	0.029	-0.024	-0.071***
	(0.016)	(0.015)	(0.021)	(0.017)	(0.019)
Unmarried Child	-0.055	-0.040	-0.078	0.067**	0.105***
	(0.041)	(0.045)	(0.056)	(0.029)	(0.039)
Other relations	-0.071**	-0.034	-0.020	0.014	0.090***
	(0.032)	(0.030)	(0.038)	(0.010)	(0.022)
Scheduled Caste	-0.068**	-0.083***	0.068	0.025	0.075**
	(0.033)	(0.028)	(0.043)	(0.022)	(0.035)
Scheduled Tribe	-0.126***	-0.029*	0.128***	0.019	0.003
	(0.022)	(0.016)	(0.022)	(0.015)	(0.020)
Other Backward Class	-0.040**	-0.021	0.017	0.005	0.026
	(0.019)	(0.016)	(0.016)	(0.014)	(0.017)
Muslim	-0.029*	-0.064***	-0.048**	0.005	0.127***
	(0.017)	(0.018)	(0.018)	(0.015)	(0.017)
Other religions	-0.052***	0.013	-0.010	0.031	0.027
	(0.016)	(0.021)	(0.017)	(0.019)	(0.019)
Primary and below	0.029	0.001	-0.090***	0.008	0.034*
	(0.020)	(0.018)	(0.023)	(0.010)	(0.019)
Upper primary and secondary	0.032*	-0.015	-0.144***	0.037***	0.082***
	(0.017)	(0.017)	(0.018)	(0.011)	(0.016)
Above secondary	0.007	-0.006	-0.182***	0.044***	0.120***
	(0.022)	(0.021)	(0.021)	(0.015)	(0.022)
Household Size	0.005*	0.000	-0.004	0.001	-0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Ever married	0.072**	-0.113***	-0.002	-0.069**	0.128***
	(0.032)	(0.032)	(0.043)	(0.031)	(0.034)
No. of Colleges	-0.000	0.000***	-0.000**	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Proportion of Technical Colleges	-0.005	0.182***	-0.173**	-0.036	0.019
	(0.051)	(0.056)	(0.069)	(0.049)	(0.051)
Urban	-0.055***	0.093***	-0.049***	-0.007	-0.004
	(0.012)	(0.012)	(0.011)	(0.009)	(0.012)
Constant	0.325***	0.237***	0.536***	0.072*	-0.138***
	(0.061)	(0.056)	(0.069)	(0.043)	(0.047)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.180	0.205	0.181	0.083	0.377
Observations	18397	18397	18397	18397	18397

Notes: This is the detailed version of Table 3. Robust standard errors are clustered at the district level in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.18: Effect of FGGS scheme on industry type (Complete estimates)

	Agriculture Sector (1)	Secondary Sector (2)	Service Sector (3)
TN × Post	-0.071**	0.016	0.067**
	(0.035)	(0.033)	(0.030)
Female	0.098***	-0.035	-0.055**
	(0.020)	(0.026)	(0.023)
Age 26 years	-0.014	0.020	0.004
	(0.025)	(0.025)	(0.030)
Age 27 years	-0.005	0.008	-0.001
	(0.024)	(0.028)	(0.032)
Age 28 years	0.059**	-0.038	-0.009
	(0.025)	(0.026)	(0.027)
Age 29 years	0.029	0.003	-0.017
	(0.022)	(0.033)	(0.033)
Unmarried Child	-0.014	-0.004	-0.001
	(0.049)	(0.050)	(0.053)
Other relations	-0.063	0.046	-0.010
	(0.042)	(0.037)	(0.035)
Scheduled Caste	0.167**	-0.105*	-0.078
	(0.067)	(0.053)	(0.047)
Scheduled Tribe	-0.007	0.091***	-0.095***
	(0.030)	(0.034)	(0.030)
Other Backward Class	-0.007	0.045*	-0.061**
	(0.024)	(0.025)	(0.028)
Muslim	-0.119***	0.011	0.103***
	(0.025)	(0.034)	(0.027)
Other religions	-0.037	-0.006	0.036
	(0.023)	(0.030)	(0.029)
Primary and below	-0.021	-0.017	0.022
	(0.027)	(0.026)	(0.027)
Upper primary and secondary	-0.045**	-0.024	0.062**
	(0.023)	(0.024)	(0.024)
Above secondary	-0.071**	-0.070**	0.130***
	(0.028)	(0.030)	(0.033)
Household Size	0.002	-0.002	0.002
	(0.004)	(0.004)	(0.004)
Ever married	0.071	-0.010	-0.049
	(0.044)	(0.051)	(0.037)
No. of Colleges	-0.001***	-0.000	0.001***
	(0.000)	(0.000)	(0.000)
Proportion of Technical Colleges	-0.259***	0.178**	0.045
	(0.069)	(0.087)	(0.066)
Urban	-0.243***	0.019	0.205***
	(0.024)	(0.022)	(0.017)
Constant	0.555***	0.212***	0.305***
	(0.071)	(0.076)	(0.071)
Controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Mean Dep Variable	0.147	0.186	0.235
Observations	10530	10530	10530

Notes: This is the detailed version of Table 4. Robust standard errors are clustered at the district level in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.19: Effect of FGGS scheme on occupation type (Complete estimates)

	Professionals (1)	Associate Professionals (2)	Secondary Occupations (3)	Elementary Occupations (4)	Others (5)
TN × Post	0.025	0.039**	0.068*	-0.043	-0.062***
	(0.017)	(0.016)	(0.041)	(0.037)	(0.019)
Female	0.046***	0.055***	-0.154***	0.116***	-0.065***
	(0.012)	(0.013)	(0.025)	(0.024)	(0.013)
Age 26 years	-0.005	0.012	0.022	-0.022	-0.005
	(0.011)	(0.013)	(0.033)	(0.027)	(0.019)
Age 27 years	-0.001	-0.009	0.012	-0.028	0.038*
	(0.011)	(0.012)	(0.030)	(0.025)	(0.022)
Age 28 years	-0.012	-0.020*	0.016	0.020	0.001
	(0.013)	(0.010)	(0.031)	(0.023)	(0.015)
Age 29 years	-0.001	-0.006	-0.014	-0.001	0.041
	(0.014)	(0.014)	(0.037)	(0.031)	(0.025)
Unmarried Child	0.022	-0.013	0.076	-0.082	-0.027
	(0.018)	(0.026)	(0.056)	(0.058)	(0.027)
Other relations	-0.017	-0.011	0.040	-0.032	-0.016
	(0.017)	(0.018)	(0.039)	(0.039)	(0.022)
Scheduled Caste	-0.046***	0.002	-0.039	0.132**	-0.002
	(0.017)	(0.021)	(0.064)	(0.065)	(0.033)
Scheduled Tribe	-0.033**	-0.024	-0.087**	0.149***	-0.024
	(0.016)	(0.015)	(0.037)	(0.034)	(0.023)
Other Backward Class	-0.011	-0.010	-0.000	0.016	-0.021
	(0.017)	(0.014)	(0.031)	(0.026)	(0.022)
Muslim	-0.037***	0.000	-0.106***	0.014	0.117***
	(0.010)	(0.014)	(0.032)	(0.021)	(0.024)
Other religions	-0.002	0.029	-0.033	-0.014	0.003
	(0.019)	(0.025)	(0.041)	(0.029)	(0.026)
Primary and below	0.009	-0.021*	0.047	-0.094***	0.031**
	(0.011)	(0.012)	(0.033)	(0.027)	(0.015)
Upper primary and secondary	0.028***	0.007	-0.001	-0.129***	0.084***
	(0.010)	(0.012)	(0.027)	(0.024)	(0.016)
Above secondary	0.103***	0.037	-0.078*	-0.165***	0.094***
	(0.022)	(0.035)	(0.040)	(0.036)	(0.023)
Household Size	-0.003	0.002	0.005	-0.000	-0.004
	(0.002)	(0.002)	(0.006)	(0.004)	(0.003)
Ever married	0.021*	-0.041	-0.009	0.021	0.025
	(0.011)	(0.026)	(0.039)	(0.041)	(0.030)
No. of Colleges	0.000***	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Proportion of Technical Colleges	-0.062	0.053*	0.114	-0.068	-0.029
	(0.039)	(0.027)	(0.110)	(0.097)	(0.071)
Urban	0.043***	0.042***	-0.034*	-0.113***	0.039***
	(0.011)	(0.009)	(0.019)	(0.019)	(0.014)
Constant	0.040	0.027	0.451***	0.407***	0.136***
	(0.035)	(0.029)	(0.088)	(0.086)	(0.051)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Mean Dep Variable	0.033	0.036	0.296	0.136	0.065
Observations	10530	10530	10530	10530	10530

Notes: This is the detailed version of Table 4. Robust standard errors are clustered at the district level in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.