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Employment Effects of Jamuna Bridge in Bangladesh

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Abstract

In this study we evaluate the impact of Jamuna multipurpose bridge (JMB) on jobs in Bangladesh. JMB is the ever largest bridge in Bangladesh, as well as the largest physical infrastructure in the history of the country, which was built and inaugurated in 1998 to provide the first road and rail link between the relatively less-developed Northwest region of the country and the more-developed Eastern half that includes the capital of Dhaka. We particularly focus on labour market integration effect of JMB using survey data from 2009 that provides information on current, as well as retrospective assessment of household situation in the adjacent districts. Using a quasi-experimental framework of the canonical difference-in- difference regression methodology, we analyse the impact of this physical infrastructure on jobs and livelihood improvement of households in two adjacent districts connected by the bridge and found that the bridge construction facilitated farm to non-farm shift of employments along with decreasing household unemployment. We also find that such impacts are heterogeneous across age, gender and education level. The study findings should inform government's policy makers on broader impacts of physical infrastructure on expansion of employment opportunities and thus help formulating evidence-based policy making on local infrastructure and labour outcomes.

Keywords: infrastructure, employment generation, occupational choices, Bangladesh

JEL Code: H54; J40; J62; O1; O18

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1. Introduction

Physical infrastructure is seen as an essential precondition for industrialization and economic development (Murphy et al. 1989). Studies show that the development of physical infrastructure improves an economy's long-term production and income levels of an economy in both the macroeconomic endogenous growth literature (Barro 1990; Futagami, Morita, and Shibata 1993) and empirical studies (Easterly and Rebelo 1993; Lipton and Ravallion 1995; Jimenez 1995; Canning and Bennathan 2000; Esfahani and Ramirez 2003; Canning and Pedroni 2008; Calderón, Moral–Benito, and Servén 2014). For example, Hulten et al (2006) found that in India, from 1972 to 1992, highways and electricity accounted for almost half of the growth of the Solow residuals of manufacturing industries. Other studies have discussed on positive productivity effects of physical infrastructure in rural and agricultural sectors (Jimenez, 1995; Fan and Zhang, 2004; Zhang and Fan, 2004). These suggest that infrastructure is likely to reduce poverty by enhancing growth, given that positive strong correlation between income growth and poverty reduction has been widely observed (see Besley and Burgess, 2003; Dollar and Kraay, 2002, Ravallion, 2001).

In fact, physical infrastructure consists of two parts—economic infrastructure such as telecommunications, roads, irrigation and electricity; and social infrastructure such as water supply, sewage systems, hospitals and school facilities. A number of micro studies have shown that development of a variety of these types of infrastructure is one of the indispensable components of poverty reduction. These include Datt and Ravallion (1998) on state-level poverty in India, Van de Walle (1996) on the poverty reduction effect of irrigation infrastructure in Vietnam, Jalan and Ravallion (2003) on water supply systems, Lokshin and Yemtsov (2004, 2005) on the poverty reduction effect of community-level infrastructure improvement projects on water supply systems in Georgia, and Duflo and Pande (2007) on the role of dams in reducing poverty in India. In addition, Brockerhoff and Derose (1996) and

Jalan and Ravallion (2003) investigate the role of water supply and public health systems. Jacoby (2000), Gibson and Rozelle (2003), and Jacoby and Minten (2009) investigate the effectiveness of road and transportation infrastructure.

While these micro-econometric studies are insightful in uncovering the role of infrastructure in reducing poverty, to best of our knowledge, only few studies explicitly approach "structures" of poverty reduction effect of infrastructure. One of such important channels should be the job transformation and non-farm employment effects of improved infrastructure because most of labour market imperfections and resulting slow structural transformations could be attributed to binding market frictions (Banerjee and Newman, 1993) which can be relaxed by infrastructure development. While there are several important studies related to this topic such as Fafchamps and Shilpi (2005), Jacoby and Minten (2009), and Bryan, Chowdhury, and Mobarak (2014), impacts of large scale infrastructure, which decrease (labour) market transaction costs surprisingly have been unexplored. Hence our study by filling this gap will have significant development policy implication.

In this study we focus on the impact of Jamuna multipurpose bridge (JMB), the largest bridge as well as the ever largest infrastructure in Bangladesh, on labour market integration. Jamuna River, one of the main water streams in Bangladesh, physically divide the country into two halves, and the Bridge was built in 1998 in order to provide the first road and rail link between the relatively less-developed Northwest region of the country and the more-developed eastern half that includes the capital of Dhaka and the port of Chittagong. Presumably, JMB connects the eastern and western part of the country, facilitating economic integration and development of the whole economy (Hossain, Sen, and Sawada, 2012).

The rest of this paper is organized as follows. In Section 2, we review the existing studies on the Jamuna multipurpose bridge, which is followed by a short literature survey on impact evaluation of infrastructure in Section 3. Section 4 explains the evaluation methodology and data adopted in this study. In Section 5, we explain empirical analysis and results which is followed by concluding remarks in Section 6.

2. Existing Literature on Impact of JMB

There are several existing (impact) evaluation reports of JMB. Luppino et al. (2004) investigate and attempt to quantify the indirect and induced impacts utilizing computable general equilibrium (CGE) and social accounting matrix (SAM) models and then take the simulation based results to feed them into poverty modules to estimate the impact of the bridge investment on national poverty levels. Both the exercises show a reduction in poverty in Bangladesh due to installation of JMB. However, the results suggest a higher magnitude of poverty reduction under the SAM approach than the CGE approach, which would hold even if a common social accounting matrix had been used in both cases. Ghosh et al. (2010) attempted to reveal the livelihood status of the project affected people (PAP) after the implementation of the project in 1998, using both quantitative and qualitative approach. Their findings suggested that though the livelihood of the PAP was affected due of loss of land, they could manage to restore their livelihood during the post-project time. Using household panel data, Bayes (2007) attempted to assess the impact of JMB in reducing poverty, finding that the construction of the bridge went a long way in reducing the poverty in Northwestern part of the country. Notably, the share of income from remittances, for functionally landless households, has been increasing and farmers in the Project villages are increasingly putting in lands under high value crops. The project completion report by ADB (2000) concluded that: "*The Project has been satisfactorily implemented and is rated highly successful. The main objective of the Project has been met, connecting the eastern and western parts of the country, separated by the Jamuna River, through a fixed link. The Project will stimulate economic growth by facilitating the transport of passengers and freight and the transmission of* *electricity, natural gas, and telecommunications across the Jamuna River ore economically and efficiently.*"

While a fact may be seen clear here, rigorous econometric works, especially on the impacts on labour market by this large infrastructure are still missing. The present study aims to fill such knowledge gap in the literature.

3. Impact Evaluation of Infrastructure

In terms of evaluating impacts of infrastructure, non-experimental studies tend to provide biased estimates of elasticity due to selection bias as infrastructure may be placed in areas where economic growth is expected and or hosting communities have appropriate capacities (see Sawada 2014 for a discussion on this). Experimental or quasi-experimental approach that can address the selection bias can establish causal impacts. For example, Gonzalez –Navarro and Quinana-Domeque (2012) provide the first randomized evaluation of street asphalting pavement on poverty reduction in Acayucan, Mexico, and show that within two years of intervention, i.e., street asphalting, households increased their consumption for durable goods and acquired more motor vehicles.

Random placement of infrastructure can prove to be difficult. However, when infrastructure placement is beyond human manipulation that provide researchers a natural experimental setting similar to DiNardo (2008), in which affected people can be assigned to treatment and control group to analyse the impact. For example, Duflo and Pande (2007) use quasi-experimental instrumental variable approach to study the impact of dams in India on poverty reduction whereby they use river gradient variable as instrument. Using district level information they show that downstream districts positively benefited with agricultural production income unlike the districts where dam is located. Using a similar identification strategy, Dinkelman (2011) studies the impact of household electricity access on employment in South Africa, whereby they use land gradient information as instrumental variable for electrification and conclude that electrification had positive impact on female employment within five years. Banerjee et al (2012) address the problem of endogenous placement of transportation network, by using historical data from Chinese cities and counties as the transport network tend to connect historical cities, to show the impact of transportation network on regional economic outcome. Sawada et al. (2014) provides support of the role of infrastructure in reducing both chronic and transient poverty using expenditure using a unique panel data from irrigated and non-irrigated areas in Southern Sri Lanka. To evaluate rural development programs in Bangladesh, Khandker et al (2009) used a household fixed-effects approach using panel data and estimated the returns to road investment in terms of its impact on household per capita consumption and found that households benefited in number of ways from road investment by paving an earthen road. They suggested that household surveys are necessary to capture the full treatment effects of road development.

4. Methodology and Data

To assess the impacts of JMB on labour market integration, we analyse the JMB evaluation data collected by BRAC-RED (Ghosh et al., 2010). We particularly focus on the occupation and employment opportunity information of the household roster to see how JMB facilitated labour market outcome. In 2009, BRAC-RED conducted an impact assessment study of JMB construction surveying households in the adjacent Sirajganj and Tangail districts in which 1,550 households were selected randomly from the identified households of Project-affected persons (PAP). The data set provides us various information of a total of 1,485 household (761 in Tangail; and 841 in Sirajganj). In addition to current information, the survey consists retrospective questions on occupation and households' assessments of their livelihood condition before bridge construction. This means that pre-bridge information is collected after ten years of the bridge construction retrospectively. We believe that such a concern is less problematic in our setting: First, we employ retrospective information on occupation which may be accurately recalled even after ten years. In fact, comparing respondent reports with company records for a sample of workers from a large manufacturing firm in the US, Mathiowetz and Duncan (1988) found that time was not found to be the most important factor in producing retrospective response errors of unemployment. Second, since variables with potential recall errors are used for independent variables, not for dependent variables, estimation biases due to measurement errors are not necessarily serious in our analysis. While a variable with measurement errors enter as independent variables in a regression model, it is natural to be concerned about attenuation bias arising from measurement errors in retrospective data, when the variable with errors is used as a dependent variable, the errors will not cause estimation bias if the errors are mean zero random errors, albeit the non-classical measurement errors.

To analyse the impact of infrastructure intervention, we can regard households in Sirajganj and Tangail districts as "treatment" and "control" groups of the bridge, respectively. This is simply because the JMB improved accessibility of Sirajganj to Dhaka dramatically although Tangail were relatively unaffected by the bridge in terms of access to Dhaka. Figure 1 (Map 1 and 2) shows the location of the bridge as well as the survey locations, respectively. In the survey Map 1 we have treated Sirajganj (point B in Map 1) and Tangail (point A in Map 1) districts as "treatment" and "control" groups respectively, to evaluate the policy impact.

Insert FIGURE 1 here

Accordingly, our data set allows us to adopt the canonical difference- in-difference approach to analyse the impact of Jamuna bridge construction on jobs and livelihoods. Difference-in difference is one of the most important identification strategies in applied economics, which model measures the differences in outcome overtime for the treatment group in interest compared to the difference in outcome overtime for the control group in interest (see Angrist and Krueger 1999 and Bertrand et al., 2004). A potential issue of our analysis is in selection bias arising from endogenous choice of the bridge location. For example, if the location is selected according to the pre-bridge density of economic activities, then there will be an upward bias in estimating the treatment effect. As Al-Hussain, Ansary, and Choudhury (2004) describe, the Jamuna Multipurpose Bridge Authority (JMBA), which was formed by the Government of Bangladesh in 1985, selected the site for the bridge near Bhuapur-Sirajganj where the river flows in a relatively narrow belt and mostly in one channel on the basis of satellite imagery and earlier bathymetric surveys. In other words, the bridge location has been decided mainly by engineering reasons. Reflecting this, the World Bank's project completion report stated that as to resettlement and rehabilitation issues, "*people do not become entitled to support until they have actually been displaced by flooding or erosion, and the amount and location of this is wholly unpredictable*" World Bank (2000). These settings indicate that the policy treatment due to the bridge construction has been largely exogenous to surrounding people's characteristics.

4.1 Balancing Tests

In order to check the exogeneity of the bridge construction formally, we conduct balancing tests of observed pre-bridge characteristics between the treatment and control groups by checking the similarity of the control and treatment groups prior to the bridge construction. Specifically, we test a null hypothesis of the same mean values for four observed variables, age, education level, and unemployment rate of the household head, and subjective income sufficiency index before the bridge construction, across treatment. Table 1 shows that there are no statistically-significant differences across treatment and control groups in these four pre-bridge variables.

4.2 Policy Effects

The data set by Ghosh et al. (2010) provides information about households' assessment of positive as well as negative aspects of JMB in term of household welfare. The survey contains the respondents' assessments of household benefit as a result of the bridge construction, whereby multiple response category were used. We focus on one particular response category in our analysis i.e., expanding employment opportunities. In fact, Ghosh et al. (2010) observed that a considerable number of people reported that it increased employment opportunity and that the property value (land price) went up in Tangail. However, in Sirajganj more people reported that it increased price of land together with increased employment and business opportunities. Here we suppose that the residents in Sirajganj are "treatment" group and those who are in Tangail are "control" group. We can then construct a treatment indicator d which takes 1(one) for Sirajgani and 0 (zero) for Tangail where d=1 shows treatment group and d=0 is control group. Then we can set up a canonical difference-in-difference model to estimate the treatment effect as follows. In a difference-in-difference model only a single variable indicates treatment, i.e., the interaction variable between treatment group and the treatment period dummy variable:

$$Y_{it} = \alpha_0 + \alpha_1 T_t + \gamma d_i + \delta T_t \times d_i + u_i + \varepsilon_{it}, \tag{1}$$

where T is a time dummy; u and ε are household fixed effects and error term, respectively. The average treatment effects on the treated can be captured by estimating δ. Let Δ shows a first order lag operator. Then we have a first-differenced version of the model (1) as follows:

(2) $$\Delta Y_{it} = \alpha_1 + \delta d_{it} + \varepsilon^{d}_{it}$$

Our estimation strategy is to estimate the treatment effect by estimating equation (2) by using OLS under a set of standard assumptions with a set of observed control variables, X. While it is unlikely that mass migrations have been induced by villages in Sirajganj, to mitigate bias arising from omitted variables, we also included village fixed effects, u_v. By doing so, we can also accommodate village specific un-parallel trends. Our final regression model is formulated as follows:

(3) $$\Delta Y_{it} = \alpha_1 + \delta d_{it} + X_{it}\beta + u_v + \varepsilon^{d}_{it}$$

As a dependent variable, Y, we employ information of households' assessments on merits from the construction of Jamuna Bridge, whereby one of the response categories is "improvements in employment opportunities." The proportion of respondents who selected this answer choice is 18.53% and 22.54% for Tangail and Sirajganj districts respectively, and the proportion is 4.01% higher (t-statistics=1.91) among the treatment group. We also have detailed job category of each individual in the data set before and after JMB. There are mainly seven job categories. This would allow us to construct a job transition matrix before and after JMB construction for each district.

To investigate the job transition patterns, we will estimate a multinomial logit model of occupational transition. Our framework is that of an additive random-utility model in which a latent equation for utility for individual i taking alternative j at time t is formulated as:

(4) $$V_{ij} = \alpha_{0j} + \alpha_{1j}T_t + \gamma_j d_i + \delta_j T_t \times d_i + X_{it}\beta_j + u_{it}.$$

This individual would take alternative j when alternative j has the highest utility of the alternatives, which is observed. It follows that Prob(y_i=j) = Prob(V_{ij}>V_{ik}) for all k. In equation (4), δ_j quantifies the choice-specific treatment effect of JMB in the non-linear difference-in-difference approach, which can be estimated by multinomial logit (MNL) model. By transferring the difference-in differences identification strategy to the latent variable, the non-linearity in the conditional expectation of the outcome is addressed. Here the latent non-linear index is contained in the interaction term that is the product of the group and time indicators, whereas the difference in difference usually referring to a difference in the differences between groups across times. As Puhani (2012) showed, the treatment effect in non-linear models is the cross difference of the observed outcome minus the cross difference of the potential non-treatment outcome, which equals the incremental effect of the interaction term coefficient in the index. To illustrate this, we have a non-linear difference-in-difference model for each of the occupation choice: $E[Y|\, T, d, X] = \Gamma(\alpha_0 + \alpha_1 T + \gamma d + \delta T\times d + X\beta)$ where Γ is a distribution function. Then as Puhani (2012) showed, the treatment effects in the difference-in-difference model can be written as:

$$(5) \qquad E[Y^1|\, T=1, d=1, X] - E[Y^0|\, T=1, d=1, X] = \Gamma(\alpha_0 + \alpha_1 + \gamma + \delta + X\beta) - \Gamma(\alpha_0 + \alpha_1 + \gamma + X\beta).$$

This indicates that the treatment effect is the cross difference of the conditional expectation of the observed outcome Y minus the cross difference of the conditional expectation of the counterfactual outcome Y^0, which can be simplified to the marginal effect of the coefficient of the interaction term, $T\times d$. The subsequent estimations will also incorporate heterogeneous treatment effects by age, gender, and education level.

5. Empirical Results

To estimate our model of equation (3), we define a discrete dependent variable which takes one if employment opportunities expanded; and zero otherwise. We adopted a linear probability model by estimating the discrete dependent variable model of equation (3) by OLS. To control for effects arising from other observables, we run a simple regression using an indicator variable of livelihood improvement which is defined as employment opportunities expansion situation after JMB. We regress this indicator variable on treatment indicator variable with or without two control variables, i.e., the incremental land size after JMB and the amount of compensations received after JMB.

Table 2 reports estimation results based on the difference-in difference model of equation (3). Specification (1) shows the overall impact of JMB whereas specification (2) is location specific treatment effects. The results indicate that JMB has a positive and significant employment improvement effects with or without an assumption of homogenous treatment effects. The results in specification (1) indicate that JMB increased possibility of employment expansion by 4% on average. The impact seems to be larger in the less adjacent areas (location #2 and #4) than the nearby location (location #1), suggesting that there might be direct negative impacts of JMB due to relocation. The qualitative results are maintained if we control for direct impact of JMB through expansion of land-holding and transfers of monetary compensations due to relocation.

5.1 Multinomial logit (MNL) results

We estimate a model of equation (4) using the multinomial logit (MNL) model. Table 3 shows estimated coefficients as well as marginal effects calculated at the mean in brackets of a simple specification of MNL, in which we consider farming or fishing as the base occupation category for comparison. The estimated results show that the common treatment effect, $T\times d$, is not significant for any of the occupational category at the 5% of significance level although specification (3) for business and trade job category shows a marginal negative impact.

Since estimation with a homogenous treatment assumption may mask important heterogeneity, we incorporate heterogeneous treatment effects with regards to age in Table 4, as well as gender and education level of respondents in Tables 5 and 6. For age, we use the following age categories: 1) 21-30 years of age, 2) 31-50 years of age and 3) 51-71 years of age. We then investigate the differential treatment effects with respect to male and female (Table 5). In a final specification reported in Table 6, we incorporate specific treatment effects for the high education group in order to see heterogeneous effect arising from human capital.

In Table 4, we observe that being young (age 21 to 30) induce transition from farming to wage labourer in category (1). This means that younger people could switch from farming to more cash rewarding daily labour and trading occupation. We also observe that more young household members could be engaged in studying (student as an occupation in category (5)). We also observe treatment effects on productive age people (age 31 to 50) having less unemployment shown in category (7)-unemployment rate of this group decreased by around 16 % points.

In Table 5, we adopted a specification allowing for further heterogeneity across genders. In this table, we find that these transition patterns among the young observed in Table 4 are rather male specific than female. JMB seems to induce the young male of age 21 to 30 to switch from farming or fishing to wage as well as business or trade occupations. However, in category (7), the effect of decreasing unemployment effects is found among female members of age 31-50 years with 20% point decrease of unemployment rate.

Finally, in Table 6, we allow heterogeneous treatment effects by education level. We define “high education group” as a group of people whose education level is equal to or higher than the higher secondary school level. In this specification, we clearly observe that the occupation transition effect of JMB from farming to day labourer is pronounced among uneducated male, and that the transition from farming to trading or commerce is concentrated among the educated male. According to category (5), the schooling effect of JMB is concentrated on educated young male.

Conclusions

This study focuses on the structures of poverty reduction effects of a large infrastructure such as job transformation and non-farm employments and the results suggest that the bridge construction on the river of Jamuna connecting the two parts of Bangladesh facilitated farm to non-farm shift of employments, while also decreased household unemployment. We also observe specific occupation transition effect according to age, gender and education level. The results have favourable policy contexts and are suggestive that supply side intervention on the part of government is necessary. This means government should facilitate opportunities such as public transportation, small business development etc. in order for people to obtain full benefit of infrastructure investment. Evidence suggest that providing cash incentives to aid transportation cost induces seasonal migration resulting in household welfare in rural Bangladesh (Bryan et al, 2014). Elsewhere it has been shown that infrastructure placements have positive impact on property value and thus facilitate access to collateral based finance and hence economic emancipation. Merely infrastructure placement may not be sufficient to maximize its potential benefits. Economic environment in poor areas can be improved through public work programs and microfinance programs to facilitate small businesses with improved road transportation as well as other infrastructure facilities. Moreover, since our results indicate that improved infrastructure access induce more schooling, such effects can be strengthened by conditional cash transfer programs to stimulate further human capital investments. However, little is known regarding how much these infrastructure improvements actually change the lives of the poor through other complementary programs. Future research should focus on more rigorous evaluation to quantify the impact of various infrastructure provision combined with other social programs as a conduit of poverty reduction in developing countries.

The study findings should inform government's policy makers on broader impacts of physical infrastructure on expansion of employment opportunities and thus help formulating evidence-based policy making on local infrastructure and labour outcomes.

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Figure 1

Impact of Jamuna Bridge: Location of Treatment and Control Areas

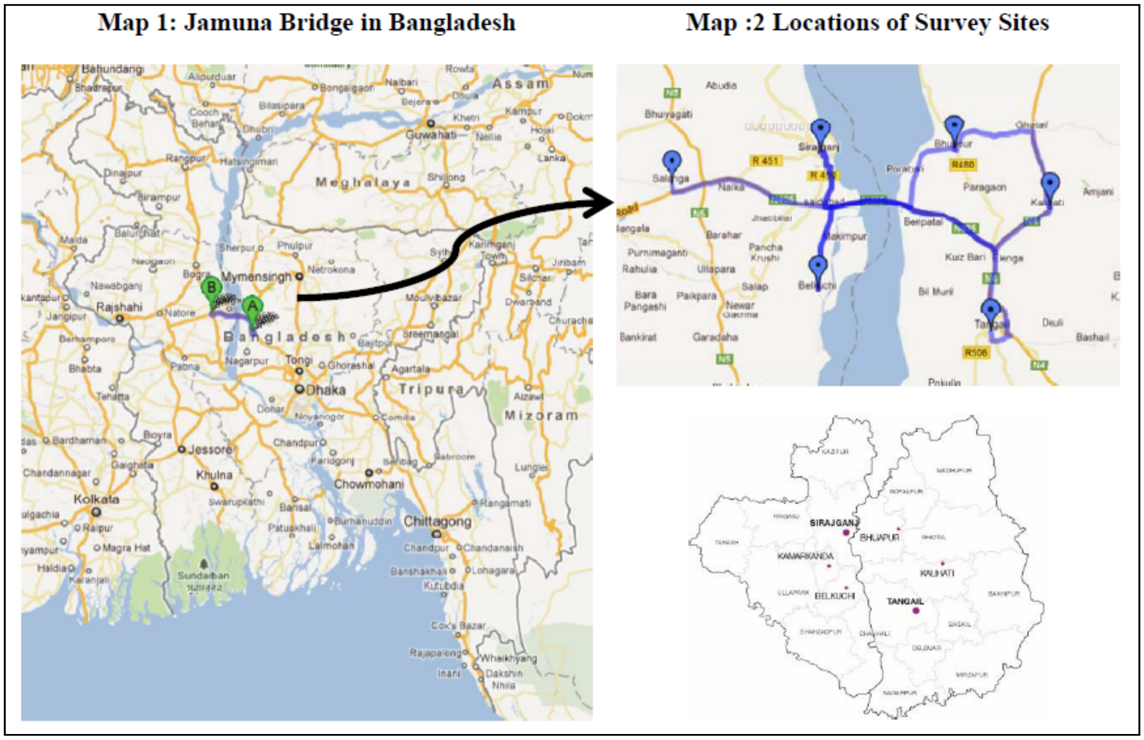

Table 1. Tests of Balancing of Baseline Observables

Variable	Treatment group	Control group	Mean difference
Age of the household head (in 2009)	51.23 (0.500)	51.10 (0.447	0.134 (0.670)
Education level of the household head (1=illiterate; 2=primary; 3=secondary; 4=post-secondary)	1.50 (0.031)	1.49 (0.031)	0.010 (0.045)
Proportion of unemployment of the household head	0.015 (0.0046)	0.015 (0.0042)	0.000 (0.006)
Subjective income sufficiency (1=always deficit; 2=sometime deficit; 3=breakeven; 4=surplus)	2.53 (0.032)	2.49 (0.031)	0.043 (0.045)

Note: Standard errors are in parentheses.

Table 2. Difference in Difference Regression: Increase in Employment Opportunities

	(1) Increased Employment	(2) Increased Employment	(3) Increased Employment	(4) Increased Employment
D	0.0401*		0.0392*	
	(0.0211)		(0.0214)	
Heterogeneous treatment effects				
d for Location#2 in Tangail		0.00462		0.00489
		(0.0285)		(0.0284)
d for Location#1 in Sirajganj		0.0215		0.0211
		(0.0295)		(0.0295)
d for Location#2 in Sirajganj		0.225**		0.223**
		(0.0975)		(0.0973)
d for Location#3 in Sirajganj		0.0658*		0.0646
		(0.0397)		(0.0397)
d for Location#4 in Sirajganj		0.817***		0.817***
		(0.0227)		(0.0230)
d for Location#3 in Tangail		-0.183***		-0.185***
		(0.0227)		(0.0229)
Increase in Land-holding			0.000198**	0.000195**
			(0.0000963)	(0.0000970)
Compensation received			0.0864	0.0852
			(0.213)	(0.215)
Constant	0.185***	0.183***	0.188***	0.186***
	(0.0136)	(0.0227)	(0.0148)	(0.0232)
N	1485	1485	1485	1485
adj. R-sq	0.002	0.006	0.002	0.007

Note: Standard errors are in parentheses. ***,**,* respectively denotes statistical significance at the 1%, 5% and 10% level. In specifications (2) and (4), Location#1 in Tangail is taken as a default category for Location dummy variables.

Table 3

Multinomial Logit (MNL) Model for Job Transition

	(1)	(3)	(5)	(6)	(7)
	coefficient standard error	coefficient standard error	coefficient standard error	coefficient standard error	coefficient standard error
$T \times d$	0.090 (0.173) [0.0412]	-0.354* (0.200) [-0.043]	0.012 (0.292) [0.016]	-0.256 (0.258) [-0.031]	-0.0351 (0.265) [0.007]
T	0.294*** (0.113)	1.065*** (0.130)	-1.964*** (0.292)	0.656*** (0.183)	0.653*** (0.179)
d	0.879*** (0.120)	0.742*** (0.150)	0.439*** (0.130)	0.505*** (0.162)	0.590*** (0.193)
Female dummy	0.711** (0.281)	1.118*** (0.290)	3.393*** (0.259)	9.316*** (0.351)	3.710*** (0.267)
Constant	-0.065 (0.079)	-0.904*** (0.102)	-0.343*** (0.084)	-4.523*** (0.274)	-2.01*** (0.139)

Note: Sample size is 7747. Standard errors are in parentheses. Marginal effects calculated at the mean are in brackets. ***,**,* respectively denotes statistical significance at the 1%, 5% and 10% level. Occupation categories used for dependent variables are: (1) day labor; (2) farming or fishing (the default category); (3) business and trade (including boatman, tailor, weaver, carpenter, singer, film market, educationalist/learning work, land measuring work/land surveyor, handicraft, mechanic, sewing work/knitwear) (4) abroad (omitted due to too few observations); (5) student; (6) household work; and (7) unemployed/retired.

Table 4

Multinomial Logit (MNL) Model for Job Transition

(With heterogeneous treatments by age group)

	(1) coefficient standard error	(3) coefficient standard error	(5) coefficient standard error	(6) coefficient standard error	(7) coefficient standard error
T×*d* for age 21 to 30	0.780*** (0.266) [0.055]	0.540* (0.287) [-0.009]	1.954*** (0.352) [0.025]	0.644* (0.371) [0.012]	0.521 (0.371) [-0.012]
T×*d* for age 31to 50	0.343 (0.215) [0.250]	-0.15 (0.242) [0.070]	-15.6 (660.1) [-0.273]	-0.289 (0.332) [0.050]	-1.474*** (0.419) [-0.159]
T×*d* for age 51 to 71	-0.653*** (0.209) [0.080]	-1.353*** (0.254) [-0.80]	-16.51 (941.3) [-0.282]	-1.049*** (0.32) [-0.025]	0.24 (0.294) [0.196]
T	0.294*** (0.113)	1.064*** (0.13)	-1.968*** (0.194)	0.639*** (0.183)	0.646*** (0.18)
D	0.879*** (0.12)	0.742*** (0.15)	0.438*** (0.13)	0.503*** (0.162)	0.589*** (0.193)
Female dummy	0.689** (0.282)	1.106*** (0.29)	3.434*** (0.26)	9.322*** (0.352)	3.738*** (0.268)
Constant	-0.0634 (0.0792)	-0.902*** (0.102)	-0.349*** (0.0841)	-4.501*** (0.274)	-2.006*** (0.14)

Note: Sample size is 7747. Standard errors are in parentheses. Marginal effects calculated at the mean are in brackets. ***,**,* respectively denotes statistical significance at the 1%, 5% and 10% level. Occupation categories used for dependent variables are: (1) day labor; (2) farming or fishing (the default category); (3) business and trade (including boatman, tailor, weaver, carpenter, singer, film market, educationalist/learning work, land measuring work/land surveyor, handicraft, mechanic, sewing work/knitwear) (4) abroad (omitted due to too few observations); (5) student; (6) household work; and (7) unemployed/retired.

Table 5

Multinomial Logit (MNL) Model for Job Transition

(With heterogeneous treatments by age group and gender)

	(1) coefficient standard error	(3) coefficient standard error	(5) coefficient standard error	(6) coefficient standard error	(7) coefficient standard error
$T{\times}d$ for male age 21 to 30	0.745***	0.502*	2.130***	-12.87	0.671*
	(0.267)	(0.289)	(0.356)	(639.4)	(0.384)
	[0.472]	[0.254]	[0.057]	[-1.106]	[0.262]
$T{\times}d$ for male age 31to 50	0.363*	-0.131	-16.74	-13.98	-1.430***
	(0.217)	(0.245)	(1626.2)	(778.6)	(0.524)
	[0.762]	[0.388]	[-0.313]	[-1.097]	[0.078]
$T{\times}d$ for male age 51 to 71	-0.662***	-1.356***	-16.95	-1.045	0.361
	(0.211)	(0.258)	(1490)	(1.058)	(0.302)
	[0.091]	[-1.001]	[-0.336]	[-0.011]	[0.265]
$T{\times}d$ for female age 21 to 30	14.14	[13.75]	13.93	13.31	12.83
	(1079.5)	(1079.5)	(1079.5)	(1079.5)	(1079.5)
	[0.654]	[0.340]	[0.034]	[0.093]	[0.114]
$T{\times}d$ for female age 31to 50	-0.162	-0.623	-16.06	-0.746	-1.986**
	(0.852)	(0.875)	(951.2)	(0.79)	(0.896)
	[0.299]	[0.090]	[-0.315]	[0.024]	[-0.201]
$T{\times}d$ for female age 51 to 71	-0.672	-1.604	-16.64	-1.541*	-0.411
	(0.891)	(0.987)	(1271.4)	(0.792)	(0.819)
	[0.178]	[-0.098]	[-0.324]	[-0.033]	[0.159]
T	0.293***	1.063***	-1.974***	0.611***	0.641***
	(0.113)	(0.13)	(0.195)	(0.185)	(0.181)
D	0.878***	0.742***	0.437***	0.499***	0.588***
	(0.12)	(0.15)	(0.13)	(0.163)	(0.194)
Female dummy	0.661**	1.103***	3.549***	9.208***	3.896***
	(0.33)	(0.34)	(0.293)	(0.382)	(0.306)
Constant	-0.0607	-0.898***	-0.360***	-4.298***	-2.039***
	(0.0793)	(0.102)	(0.0845)	(0.28)	(0.143)

Note: Sample size is 7747. Standard errors are in parentheses. Marginal effects calculated at the mean are in brackets. ***,**,* respectively denotes statistical significance at the 1%, 5% and 10% level. Occupation categories used for dependent variables are: (1) day labor; (2) farming or fishing (the default category); (3) business and trade (including boatman, tailor, weaver, carpenter, singer, film market, educationalist/learning work, land measuring work/land surveyor, handicraft, mechanic, sewing work/knitwear) (4) abroad (omitted due to too few observations); (5) student; (6) household work; and (7) unemployed/retired.

Table 6 Multinomial Logit (MNL) Model for Job Transition

(With heterogeneous treatments by age group, gender, and education level)

	(1)	(3)	(5)	(6)	(7)
T×*d* for male age 21 to 30	0.892***	-0.0673	-0.55	-18.84	-0.508
	(0.303)	(0.343)	(0.779)	(1312.1)	(0.502)
	[1.400]	[0.742]	[0.020]	[-2.885]	[0.252]
T×*d* for male age 31to 50	0.497**	-0.596**	-17.56	-19.32	-1.761***
	(0.226)	(0.268)	(2206.4)	(1056.4)	(0.521)
	[1.464]	[0.755]	[-0.100]	[-2.866]	[0.191]
T×*d* for male age 51 to 71	-0.493**	-1.717***	-17.8	-5.750***	-0.114
	(0.219)	(0.292)	(2085.2)	(1.017)	(0.302)
	[0.432]	[0.013]	[-0.117]	[-0.736]	[0.152]
T×*d* for male age 21 to 30 (high education group)	-0.665	1.214**	3.429***	0.327	1.446**
	(0.501)	(0.5)	(0.862)	(2135.2)	(0.652)
	[-0.318]	[0.218]	[0.023]	[0.009]	[0.107]
T×*d* for male age 31to 50 (high education group)	-2.467***	1.546***	-4.912	-4.912	-22.59
	(0.711)	(0.455)	(61521.1)	(29455.5)	(86145.6)
	[0.347]	[1.175]	[-0.010]	[-0.262]	[-1.755]
T×*d* for male age 51 to 71 (high education group)	-3.115***	1.190***	-1.09	-14.9	-0.107
	(1.054)	(0.441)	(8108.6)	(3751.7)	(0.52)
	[0.147]	[1.105]	[0.018]	[-2.100]	[0.316]
T×*d* for female age 21 to 30	16.05	14.29	1.321	18.48	17.15
	(2020.3)	(2020.3)	(3017.8)	(2020.3)	(2020.3)
	[0.773]	[0.124]	[-0.091]	[0.875]	[0.312]
T×*d* for female age 31to 50	0.487	-0.0158	-13.73	3.489***	1.417*
	(0.788)	(0.854)	(1453.4)	(0.72)	(0.845)
	[-0.118]	[-0.199]	[-0.107]	[0.491]	[0.053]
T×*d* for female age 51 to 71	-0.0239	-0.932	-14.29	2.741***	2.992***
	(0.829)	(1.014)	(1921.4)	(0.722)	(0.762)
	[-0.161]	[-0.323]	[-0.108]	[0.424]	[0.233]
T×*d* for female age 21 to 30 (high education group)	-16.65	2.188	17.62	-0.172	-0.338
	(3960.1)	(3370.5)	(4047.9)	(3370.5)	(3370.5)
	[-3.919]	[1.687]	[0.166]	[0.903]	[0.433]
T×*d* for female age 31to 50 (high education group)	-1.088	17.02	15.05	15	-1.981
	(5708.8)	(4521.9)	(6909.2)	(4521.9)	(8359.2)
	[-2.498]	[2.497]	[0.064]	[1.610]	[-0.761]
T×*d* for female age 51 to 71 (high education group)	-0.577	18.43	15.61	15.59	-3.557
	(12674.6)	(10039.6)	(15119.2)	(10039.6)	(18559.2)
	[-2.484]	[2.717]	[0.065]	[1.632]	[-0.949]
T	0.288**	1.054***	-2.075***	0.326***	0.516***
	(0.113)	(0.13)	(0.187)	(0.0945)	(0.167)
D	0.878***	0.740***	0.420***	0.455***	0.568***
	(0.12)	(0.15)	(0.121)	(0.107)	(0.185)
Constant	-0.0435	-0.862***	0.126*	0.925***	-1.402***
	(0.0788)	(0.101)	(0.0756)	(0.0651)	(0.124)

Note: Sample size is 7747. Standard errors are in parentheses. Marginal effects calculated at the mean are in brackets. ***,**,* respectively denotes statistical significance at the 1%, 5% and 10% level. Occupation categories used for dependent variables are: (1) day labor; (2) farming or fishing (the default category); (3) business and trade (including boatman, tailor, weaver, carpenter, singer, film market, educationalist/learning work, land measuring work/land surveyor, handicraft, mechanic, sewing work/knitwear) (4) abroad (omitted due to too few observations); (5) student; (6) household work; and (7) unemployed/retired.

Annex-1

Transition Matrix of Job Categories for Tangail

Before JMB (B. Column 8) and After JMB (B. Column 7)
(Frequency and Cell Percentage)

Occupation 1998	Occupation 2009: 1	2	3	5	6	7	Total
1	238	14	45	0	4	14	315
	11.51	0.68	2.18	0.00	0.19	0.68	15.24
2	41	225	44	0	1	17	329
	1.98	10.89	2.13	0.00	0.05	0.82	15.92
3	8	12	103	0	2	14	139
	0.39	0.58	4.98	0.00	0.10	0.68	6.72
5	44	19	115	37	132	26	373
	2.13	0.92	5.56	1.79	6.39	1.26	18.05
6	5	0	12	1	778	34	830
	0.24	0.00	0.58	0.05	37.64	1.64	40.15
7	14	4	13	1	41	8	81
	0.68	0.19	0.63	0.05	1.98	0.39	3.92
Total	350	274	332	39	958	113	2,067
	16.93	13.26	16.06	1.89	46.35	5.47	100.00

Codes: (1)Day labor; (2) Farming or fishing; (3)Business and service (including boatman, tailor, weaver, carpenter, singer, film market, educationalist/learning work, land measuring work/land surveyor, handicraft, mechanic, sewing work/knitwear) (4) Abroad (omitted due to only single observation); (5)Student; (6) Household work; (7) Unemployed/retired

Annex-2
Transition matrix of job categories for Sirajganj
Before JMB (B. Column 8) and After JMB (B. Column 7)
(Frequency and Cell Percentage)

Occupation 1998	Occupation 2009: 1	2	3	5	6	7	Total
1	342	16	26	0	0	19	403
	18.93	0.89	1.44	0.00	0.00	1.05	22.30
2	28	97	27	0	4	19	175
	1.55	5.37	1.49	0.00	0.22	1.05	9.68
3	25	12	105	0	2	11	155
	1.38	0.66	5.81	0.00	0.11	0.61	8.58
5	50	10	84	33	106	19	302
	2.77	0.55	4.65	1.83	5.87	1.05	16.71
6	11	2	8	0	643	32	696
	0.61	0.11	0.44	0.00	35.58	1.77	38.52
7	27	6	7	1	24	11	76
	1.49	0.33	0.39	0.06	1.33	0.61	4.21
Total	483	143	257	34	779	111	1,807
	26.73	7.91	14.22	1.88	43.11	6.14	100.00

Codes: (1)Day labor; (2) Farming or fishing; (3)Business and service (including boatman, tailor, weaver, carpenter, singer, film market, educationalist/learning work, land measuring work/land surveyor, handicraft, mechanic, sewing work/knitwear) (4) Abroad (omitted due to only single observation); (5)Student; (6)Household work; (7) Unemployed/retired

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