WIDER Working Paper 2016/123

Links between foreign direct investment and human capital formation

Evidence from the manufacturing sector in India

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November 2016

Abstract: This paper is related to the literature on the effect of foreign direct investment (FDI) on the labour market of host countries. Labour market literature has focused on the demand side of FDI; that is, increasing wage inequality by demanding more skilled workers or just increasing the overall average wages. On the supply side, FDI can enrich the skilled labour force of the host country by provision of on-the-job training or learning or through indirect technological spillover effects. This paper takes into account both these effects and tests for human capital formation effect of FDI in India for core manufacturing sector firms for the period 2001–15 using the Prowess database of the Centre for Monitoring Indian Economy. It also takes into account the endogeneity of decision-making on the part of foreign firms in locating FDI. Five different determinants of FDI are used: market size, distance from main market area, length of national highways, availability of non-agricultural land, and a cast and religion fractionalization index. The most significant factor determining FDI is market size and the distance from main market area and fractionalization index. Different dynamic panel data methods are used with static and dynamic generalized method of moments techniques. This study does not find any positive supply side human capital formation effects of FDI, but finds positive demand side effect of FDI of raising wage inequality and average wages. The results remain robust while taking into account heterogeneities at region, industry, size, and age of the firms.

Keywords: foreign direct investment, human capital, labour demand, labour supply, wages
JEL classification: F24, J31, J24

Acknowledgements: I wish to thank the United Nations University World Institute for Development Economic Research (UNU-WIDER), Helsinki, for support during the PhD internship, where this study was completed. I thank my mentor Miguel Niño-Zarazúa for insightful discussions. I also thank Sugata Matjit, Smriti Sharma, and the participants at the internal seminar at UNU-WIDER for very useful comments.

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This study has been prepared within the UNU-WIDER PhD internship programme.

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ISSN 1798-7237 ISBN 978-92-9256-167-3

Typescript prepared by Ayesha Chari.

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The Institute is funded through income from an endowment fund with additional contributions to its work programme from Denmark, Finland, Sweden, and the United Kingdom.

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1 Introduction

Countries first bought the idea of foreign direct investment (FDI) as they found it a convenient and fast tool to finance their growth process without having to invest their own resources, especially in case of financial constraints. However, the strategy to benefit from FDI could also go wrong and hurt the already protected industries in economies worldwide. Having done the cost–benefit analysis, economies slowly started opening up to multinational enterprises. At the time of writing, almost three decades of literature has been developed on FDI's impact on host economies. The topic gained attention owing to its propitious impact on macro and micro economic factors. The reform process in India began after 1990 with the opening up of sectors for foreign capital as a result of easing the regulatory environment for different industries. Since then, FDI in India has surged from US$2428 million in 2000 to US$712,587 million in 2016 (see DIPP 2016a). The literature on the effect of FDI on host countries is diverse.

The literature on macro-economic effects tried to identify possible channels of increases in the economic growth of host countries, such as investment, technologies, and financial capabilities (Agosin and Mayer 2000; Borensztein et al. 1998; de Mello 1999). However, many studies also focused on the micro economic impacts of FDI on host countries. One of the most significant micro impacts is productivity gain from FDI. Although indirect, yet the most explored channel of this effect is estimation of productivity increases via production function to find support for the possible technology transfers from foreign firms to domestic firms, formally called 'spillover effects'. The results vary from developed to developing countries. Javorcik (2004) reports successfully finding positive spillovers to domestic firms for the case of Lithuanian firms through backward linkages in upstream sectors. Blomström (1986) finds competition between foreign and domestic firms to be a channel of productivity increases in modern sectors of Mexican economy. Keller and Yeaple (2009) find stronger positive productivity gains than importing spillovers for manufacturing firms in the United States. Girma and Görg (2005) report that, for a set of firms in the United Kingdom, absorptive capacity matters for productivity gain of foreign technology, and can be plotted with a U-shaped curve. Haddad and Harrison (1993) find less productivity dispersions in sectors with presence of foreign firms but no evidence of productivity gains for Moroccan firms. In the developing and emerging market economies, Aitken and Harrison (1999) find that joint ventures create spillover effects for Venezuelan plants. Dua et al. (2011) test spillover effects of foreign firms on labour productivity of Indian manufacturing firms for 2000–07. They test for inter-cluster technology spillovers in ten clusters across India. Their results show variation across clusters, with some clusters found to have positive effects of spillover compared with others. In contrast, Sasidharan and Kathuria (2011) find no significant horizontal spillover effects of FDI.

Along with productivity spillovers, direct effects on the labour market come from FDI affecting human capital of host countries. Foreign firms form skills by providing on-the-job training to their employees. Tan and Batra (1997), using firm level data for Colombia, Mexico, and Taiwan, find that large export manufacturing, high-technology firms are more likely to invest in training a more educated, more skilled, and unionized labour force than domestic firms. Ritchie (2002) sketches Southeast Asian countries' experience of training provided by multinational enterprises (MNEs). Inward FDI also raises level of human capital indirectly by subsequent spillovers to other firms via labour turnovers and spin-offs (Blomström 1986; Caves 1974; Markusen 1995). Kathuria (2001) discusses positive spillover effects of foreign firms on the productivity of domestic firms in India using panel data for 368 medium- and large-sized Indian manufacturing firms for the period 1975–76 to 1988–89. In the long term, they contribute to the general-equilibrium incentive of individuals in host countries to acquire skills through education and/or training. If individuals in host countries have access to these methods of skills acquisition, then they should respond to the price signals coming from the labour market (Slaughter 2002).

The existing political system also plays a key role in processing the effect of multinational enterprises on the labour market. According to Kapstein (2002), the political economy pathways are responsible for the effects of MNE training policies. The role of policy design and its implementation by government is significant here to tailor coordinated policies required for skill upgradation. Government help in creating human capital comes at three levels: (i) general supply of technically trained resources, (ii) matching supply and demand through active firm participation in education and training systems, and (iii) encouraging indigenous firms and MNEs to upgrade technology over time. Countries are investing in new ways of education by improving the coherency of demand and supply of required skills with integrated relationships between educational institutions and industries. Governments can also provide incentives to firms for training that would efface market failures of information constraints, credit constraints, and labour turnovers. However, the roots of vocational training systems depend on a fully developed general education system. As an example, Singapore has a reformed educational and training system with a bias towards technological, scientific, and industrial skills. It has tied the vocational training system to specific industrial sectors and skill needs, especially at the tertiary level. It has formulated a single national education system, selected English as a medium of instruction, mandated 12 years of education, and focused the curriculum on technology. Singapore's Skill Development Fund, Malaysia's Human Resource Development Fund, and the Penang Skill Development Centre represent coordination among government, business, and academia in supplying skills. Financial incentives, public research institutes, and local supplier upgrading are other ways of encouraging private firms to invest in training (Ritchie 2002: 28). A case study of Argentinian human capital formation by Narula and Marin (2005) brings forth the evidence that more skilled employment in MNEs compared with domestic firms, and firms with higher level of absorption created by high investments in training, experience more spillover effects.

Besides these supply side effects, FDI also affects the demand for labour in host countries either on average or relative wages. The literature is replete with effect of FDI on wage inequality especially for developing countries. Feenstra and Hanson (1997) find increases in skilled wages for Mexican workers relative to unskilled workers, and this increase is related to increases in FDI in Mexico's manufacturing sector by multinationals in the United States for the period 1975–88. Figini and Görg (2006) find non-linear effect of FDI on wage inequality for a panel of 100 OECD (Organization for Economic Cooperation and Development) and non-OECD countries for the period 1980–2002. Using generalized method of moments (GMM) with internal instruments their study finds that non-OECD countries initially show a positive trend of increase in wage inequality but this effect reduces with time. On the other hand, OECD countries experience a reduction in wage inequality over time and do not show a non-linear effect. Indian wage inequality has been widely studied (Azam 2010; Chamarbagwala 2006; Hasan et al. 2007; Ramaswamy 2008). This paper attempts to take into account both demand and supply effects and test for human capital formation in the Indian manufacturing sector. The paper is organized as follows. Section 2 shows the trend of FDI in India. Section 3 sketches the human capital formation. Section 4 discusses the theoretical framework, with subsections dealing with the issue of endogeneity and instruments. Section 5 discusses data and distribution of firms. Results and discussion appear in Section 6, and Section 7 concludes.

2 Trend of FDI in India

FDI in India has soared over the years with cumulative FDI inflow of US$424,167 from April 2000 to March 2016 (Table 1). Currently, an Indian firm is allowed to receive FDI under two routes: one is the *automatic route*, where no prior permission is required for investment; foreign firms can invest on the basis of different sectoral caps changed by the government from time to time. The other is the *government route*, for sectors not covered under the automatic route; here, firms require applying to the Foreign Investment Promotion Board, Department of Economic Affairs, Ministry of Finance, Government of India, to get approval.[1] The movement of sectors from government route to automatic route was slow but gained momentum after 2000 and especially after 2006 when FDI jumped from US$4029 million to US$22,826 and to US$55,457 in 2016 (DIPP 2016b).

Table 1: Foreign direct investment (FDI) inflow to India (March 2001–April 2016)

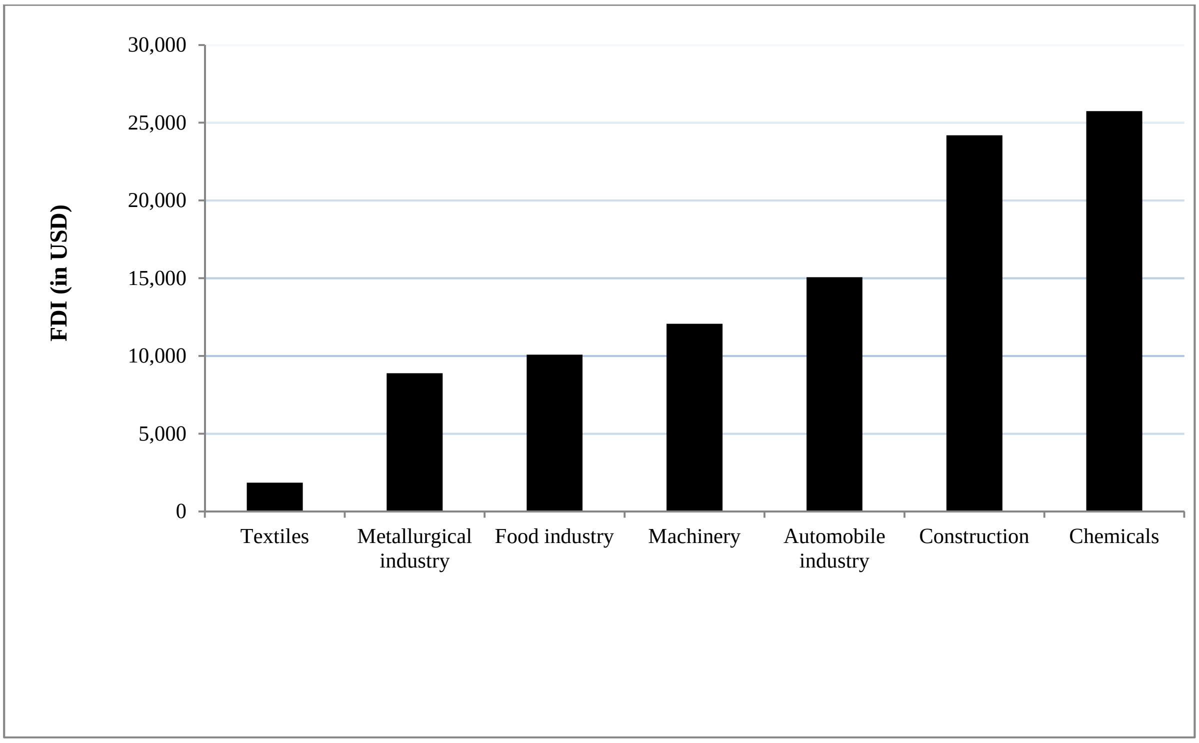
Financial year	FDI inflow (in US$ million)	Percentage change in FDI flow over previous year
2000–01	2463	
2001–02	4065	+65
2002–03	2705	–33
2003–04	2188	–19
2004–05	3219	+47
2005–06	5540	+72
2006–07	12,492	+125
2007–08	24,575	+97
2008–09	31,396	+28
2009–10	25,834	–18
2010–11	21,383	–17
2011–12	35,121	+64
2012–13	22,423	–36
2013–14	24,299	+8
2014–15	30,931	+27
2015–16	40,001	+29

Source: FDI factsheets (DIPP 2016b).

Figure 1 depicts the distribution of FDI across different sectors from January 2000 to March 2016. There was some fluctuation in FDI inflows as shown by the percentage changes in FDI inflow, with the maximum positive upsurge occurring in 2006. Construction, automobiles, pharmaceuticals, chemicals, and metal are the sectors attracting the largest FDI in the manufacturing sector after the services sector. As shown in Figure 1, FDI is more concentrated in the chemicals, automobile, construction, and machinery industries compared with textiles, food and metallurgical industries. Drawing inference from Figure 1, FDI seems to be more concentrated in the heavy industries or those requiring a high-skilled labour force.

[1] For frequently asked questions on foreign investments in India, see Reserve Bank of India (2015).

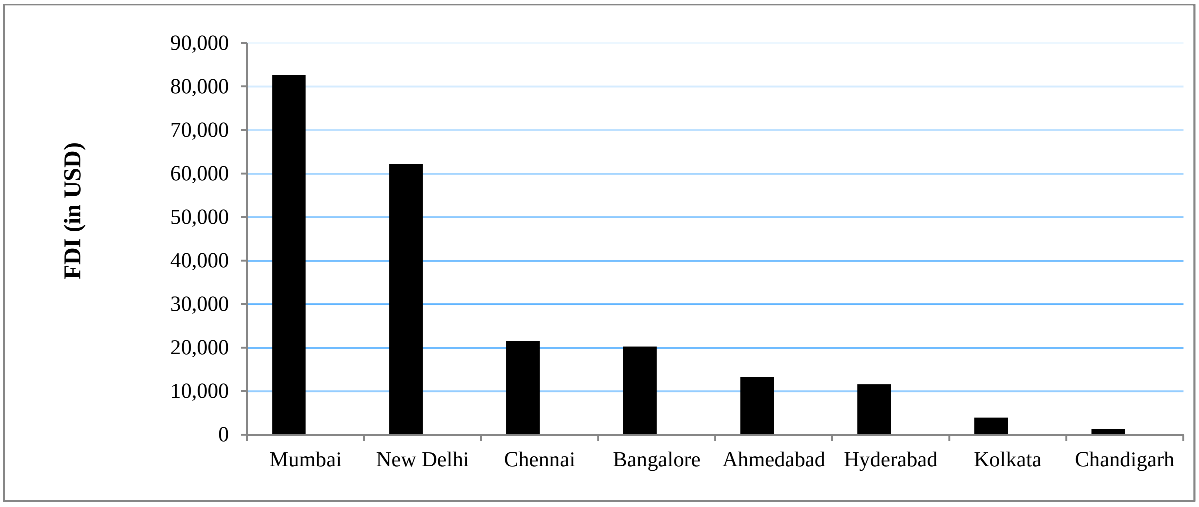
Figure 1: Subsector-wise distribution of foreign direct investment (FDI) (in USD) in the manufacturing sector in India (January 2000 to March 2016)



Source: Author's compilation based on FDI Statistics, Department of Industrial Policy & Promotion, Government of India.

Geographically, FDI is clustered in some economically advanced regions that have attracted/accounted for the largest share of FDI inflows. These include the regions of Mumbai, New Delhi, Chennai, Bangalore, Ahmedabad, and Hyderabad. On the other hand, regions such as Kanpur, Bhopal, Patna, Bhubaneswar, Jaipur, and those of the North East have received a very small amount of FDI inflow. Figure 2 shows the region-wise distribution of FDI for the period January 2000 to March 2016.

Figure 2: Region-wise distribution of FDI (in USD) in India (January 2000 to March 2016)

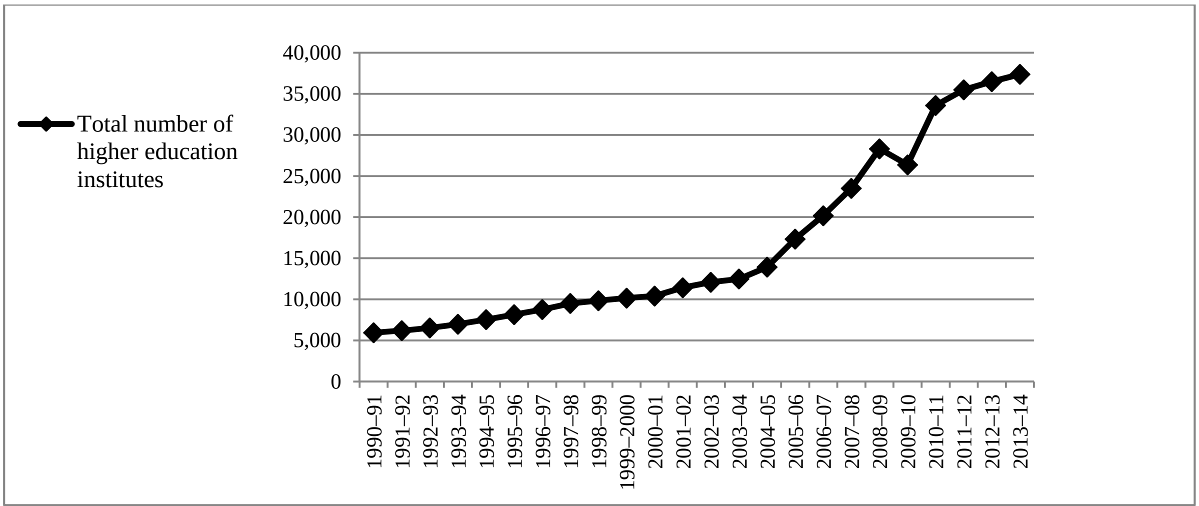


Source: Author's compilation based on FDI Statistics, Department of Industrial Policy & Promotion, Government of India.

3 Human capital formation in India

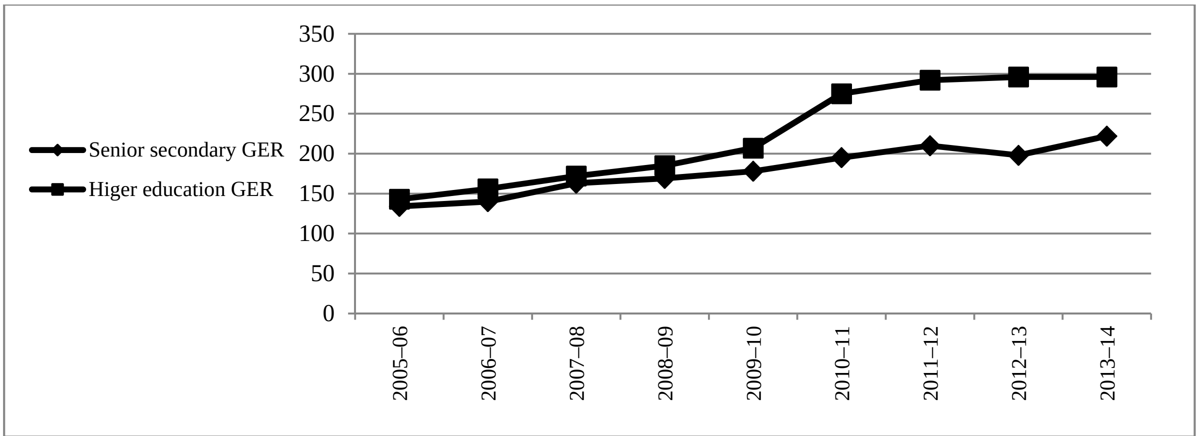
Ghosh (2016) find evidence of a large demographic dividend for the backward Indian states for the period 1961–2011. Large states such as Uttar Pradesh, Madhya Pradesh, Rajasthan, and Haryana are found to have the highest demographic dividend. Aiyar and Mody (2011) find that the demographic dividend can contribute to two percentage points annually to the gross domestic product over the next two decades—from 2020 to 2030—owing to increases in working age population. Human capital has increased over the years. Figure 3 depicts the increase in total number of higher education institutes in India over the years. This includes available total colleges and universities across the country. Similarly, there has been an increase in gross enrolment ratios in senior secondary and higher education levels over the last decade from 2000 to 2014.

Figure 3: Human capital formation in India (1990–2014)



Source: Author's illustration based on data from MHRD (2014).

Figure 4: Human capital trend (gross enrolment ratios, GERs, in secondary and higher education) in India



Source: Author's illustration based on data from MHRD (2016).

4 Theoretical setup

This paper is led by theoretical modifications Katz and Murphy (1992) and Te Velde and Morrissey (2004). Assume a two-factor constant elasticity of substitution production function with low-skilled labour (U) and high-skilled labour (S) as two inputs:

$$f(U_t, S_t) = \left\{ \lambda (\psi_{Ut} U_t)^{\rho} + (1-\lambda)(\psi_{St} S_t)^{\rho} \right\}^{\frac{1}{\rho}} \tag{1}$$

$$\varphi_{Ut} \equiv \ln \psi_{Ut}; \varphi_{Ut} = \gamma_{1U} t + \gamma_{2U} FS; \varphi_{St} \equiv \ln \psi_{St}; \varphi_{St} = \gamma_{1S} t + \gamma_{2S} FS, \tag{2}$$

where $\varphi_{Ut} \equiv \ln \psi_{Ut}$ and $\varphi_{St} \equiv \ln \psi_{St}$ are functions of labour efficiency units and parameter $\rho<1$. We can interpret labour efficiency index in terms of accumulated human capital. The elasticity of substitution between U and S is $\sigma = 1/1-\rho$. There can be many changes in technology as a result of different factors such as FDI and interaction terms of FDI with various firm level characteristics. In other words, these are some ways by which FDI can affect the labour market. These demand shift factors can include FDI and international trade.[2] The labour efficiency indices are a function of share of foreign promoters in equity shares *FS* (Te Velde 2001), interaction term $FS_{it} \times train_{it}$, and firm level factors such as training expenses and size.[3] This study includes interaction term *FDI*×*training expense* of firms to assess the human capital formation process undertaken by foreign firms.

Solving for first-order condition and keeping marginal productivity equal to factor prices gives the formula for relative wages of skilled–unskilled labour:

$$\ln\left(\frac{w_{St}}{w_{Ut}}\right) = \ln\left(\frac{1-\lambda}{\lambda}\right) - \frac{1}{\sigma}\ln\left(\frac{S_t}{U_t}\right) + \frac{\sigma-1}{\sigma}\lambda_1 FS_t + \varepsilon_t, \tag{3}$$

where $\gamma_1 = \gamma_{1S} + \gamma_{1U}$ and $\gamma_2 = \gamma_{2S} + \gamma_{2U}$; thus, wage inequality is the function of a supply term (relative supply of high- to low-skilled labour and FDI, i.e. foreign share). γ_1 shows the effect of FDI on wage inequality, and a positive (negative) γ_1 tends to increase (decrease) wage inequality.

The starting point of estimation is the demand and supply Equation (4), where demand is the dependent variable of relative wages and supply is the independent variable of relative employment with other control variables.

$$\begin{aligned} \ln\{rlw\}_{ijdst} &= \alpha_i + \beta_1 \ln\{rlemp\}_{ijdst} + \beta_2 FS_{ijdst} + \beta_3 train_{ijdst} + \beta_4 FS_{ijdst} \\ &\times train_{ijdst} + \beta_5 size_{ijdst} + \beta_6 size^2_{ijdst} + u_i + v_j + \rho_d + \sigma_S + \varsigma_t + \varepsilon_{it} \end{aligned}, \tag{4}$$

The problem with the estimation of this equation is that existence of demand and supply variables in the same equation creates endogeneity in the system. As we are not interested in

[2] For more detail on the effect of foreign direct investment (FDI) on wage inequality, see Chamarbagwala (2006), Feenstra and Hanson (1997), Figini and Görg (2006), Görg and Stroble (2002), and Ramaswamy (2008).

[3] Kathuria (2001) also empirically tests the interaction term *foreign share*×*research and development* indices.

identifying demand and supply curves but rather in estimating the human capital formation effect of FDI, the relative employment term is dropped from Equation (4) to give Equation (5):[4]

$$\begin{aligned}\{rlw\}_{ijdst} &= \alpha_{ijdst} + \beta_1 FS_{ijdst} + \beta_2 train_{ijdst} + \beta_3 FS_{ijdst} \times train_{ijdst} + \beta_4 size_{ijdst} \\ &+ \beta_5 size^2_{ijdst} + u_i + v_j + \rho_d + \sigma_S + \varsigma_t + \varepsilon_{it}\end{aligned} \quad . \tag{5}$$

The underlying assumption now is that relative employment is given and the aim is to estimate the changes in relative wages caused by FDI, on-the-job training, and other firm level factors and their interaction terms. The dependent variable is relative wages, which represents labour demand. It is a ratio of skilled to unskilled wages; it is also a ratio of wages and salaries paid by firms, as documented in the Prowess database (CMIE 2016), to the average wages of the rural sector[5] for men at an all-India level, as recorded by the Labour Bureau (2012–13) and the Reserve Bank of India (n.d.). The main independent variables are FDI, on-the-job training, size, and size squared. The focus is on the coefficient of interaction term of *foreign share*×*training* or the coefficient β_3. This coefficient measures the effect of training expenses for different values of foreign share on relative wages; β_1 measures the effect of foreign share on relative wages with zero on-the-job training expenses and β_2, the effect of training expenses with foreign share equal to zero. Thus, the interaction term allows us to look at the respective demand and supply side effects of FDI on the labour market. A positive coefficient of β_3 would indicate that the supply side effects of FDI are not strong enough to mitigate the demand side effect, resulting in wage inequality. Tables 2 and 3 present summary statistics and validity test results used in this model (for a definition of all variables, see Appendix A).

Table 2: Summary statistics

Variables	Mean (1)	Standard deviation (2)	Minimum (3)	Maximum (4)
Foreign share	26.12	26.10	0	96.8
Training	25.99	92.02	0	1630.1
Foreign share×Training	901.16	4290.44	0	67,681.75
Size	4749.66	25,584.40	0	77,6324.1
Size^2	6.77e+08	1.32e+10	0	6.03e+11
Relative wages (rural)	1.60	5.36	0	76.55
Relative wages (industrial)	1.10	3.51	0	66.68
Instruments				
Log population	17.96	0.82	12.40	19.11
Log market distance	1.73	2.48	0	10.65
Log non-agricultural land	14.63	5.42	4.77	23.02
Log length of national highways	3.81	3.11	0	42
Fractionalization	0.96	0.05	0.48	0.99

Source: Author's compilation based on study dataset.

Equation (5) can be estimated with pooled ordinary least-squares estimators, but the estimates can be biased and inconsistent. As firm level data are available, another option is applying the fixed-effects estimation taking into account the unobserved fixed effects. However, the problem still persists if there is an endogenous variable in Equation (5), say FS_{it}, which causes correlation between FS_{it} and ε_{it}. This leads us to use the instrumental variable (IV) estimation strategy that allows introducing external instruments and takes care of the possible endogeneity in the system.

[4] The log specification is also dropped as the focus is not on estimating the elasticity of substitution.

[5] The rural sector includes activities such as ploughing, sowing, weeding, transplanting, harvesting, winnowing, threshing, picking, well digging, and cane crushing; it also consists of herdsmen, carpenters, blacksmiths, cobblers, masons, tractor drivers, sweepers, and unskilled labourers (Labour Bureau 2012–13).

Table 3: Test results for validity of instruments

Instruments	Montiel–Pflueger robust weak instrument test
Log of population	10.780
Log of non-agricultural land	6.572
Log of distance from main market area	10.953
Log national highways	9.696
Fractionalization index	9.526

Source: Author's compilation based on study dataset.

For IV regressions, the following models are used:

$$FS_{ijdst} = \alpha_{ijdst} + \beta x_{ijt} + \vartheta z_{st} + u_i + v_j + \rho_d + \sigma_s + \varsigma_t + e_{it}, \quad (6)$$

$$rlw_{ijdst} = \alpha_{ijdst} + \beta x_{ijdst} + \phi FS_{ijdst} + u_i + v_j + \rho_d + \sigma_s + \varsigma_t + \varepsilon_{it}, \quad (7)$$

where z_{st} consists of a vector of strictly exogenous IVs that are partially correlated with FS_{ijt} and uncorrelated with rlw_{ijt}. More formally, $\vartheta \neq 0$ and the covariance $cov(z_{ijt}, e_{it}) \neq 0$; thus, z_{ijt} is correlated with FS_{ijt} and $cov(z_{ijt}, \varepsilon_{it}) = 0$, but uncorrelated with rlw_{ijt}. However, it is difficult to come up with a strong instrument that can serve as a proxy for foreign share. Here, the Montiel–Pflueger test for weak instruments is used (see Pflueger and Wang 2015), which is also an extension of Stock and Yogo (2002), to compare estimator 'Nagar bias' relative to 'worst case' benchmark two-stage least squares (2SLS) and limited information maximum likelihood (LIML) estimator with a single endogenous variable, *foreign share* in this case. The rejection of the test depends on effective F statistic that exceeds critical value significance level of α and desired threshold τ.

Different methods of static IV estimation are explored to check for the robustness of study results. 2SLS, GMM, LIML, continuously updated estimator (CUE), IV fixed effects, and extended 2SLS are applied.

However, there can be other sources of endogeneity in the system, which leads to incorporating the endogeneity in other variables thus giving more robust estimates. Dynamic system GMM is applied and analysis is extended by including the external instruments in a dynamic setting. Thus, the equation now becomes:

$$rlw_{ijdst} = \alpha_{ijdst} + \varphi rlw_{ijdst-1} + \beta x_{ijdst} + \phi FS_{ijdst} + u_i + v_j + \rho_d + \sigma_s + \varsigma_t + \varepsilon_{it}, \quad (8)$$

where ϕ is the parameter estimate of the lagged dependent variable $rlw_{ijdst-1}$. The Blundell–Bond system GMM is used for estimating Equation (8) (see Blundell and Bond 1998). The superiority of this estimator comes from the fact that it uses the information from lagged differential instruments to solve the level equation and then uses the lagged levels of endogenous variables as instruments for the first differential equation (Gisselquist et al. 2016).

4.1 Instruments set

The effect of FDI—crucial for economic growth literature—is also grounded in the characteristics of a host country. Alfaro et al. (2004) report that developed financial markets may help host countries gain from FDI. Using cross-country analysis, they support the idea that countries with better financial systems can provide credit to entrepreneurs and thus benefit from FDI via backward linkages. They also find that the presence of high-skilled human capital helps benefit from FDI. Borensztien et al. (1998), using cross-country data for developing countries, find that economic growth effects of FDI are stronger than domestic investment effects given the presence of good quality human capital. In the work by Noorbakhsh et al. (2001), the decision to invest in a host country may depend on the level of human capital in an economy. They measure human capital as enrolments in secondary education, and find that human capital is a significant determinant of FDI for the period 1980–94 for 36 developing countries.

The present study takes into account that FDI inflow in a host country is dependent on many factors including size of the market in the host country and availability of cheap resources. This allows the use of various available instruments at state level: five different instruments are used to check the validity of Equation (5).

Size of market is a strong determinant of inward FDI in a host country. Nunnenkemp and Mukim (2011) find 1 per cent increase in market size increases the chance of attracting an investor by 16 per cent. The idea is related to scale of economies: the larger the size of market, the larger is the incentive for a foreign firm to expand and enjoy the economies of scale by increasing production. Log of population is used to instrument for FDI.

Distance from main market area can affect the costs of a firm. Firms will always try to reduce the distance between the manufacturing plant and the main market area. The economies of scale work here too. Thus, firms will try to be located nearest a market area. The distance between the manufacturing plant and the main market area in the particular state is used to instrument for FDI.

Good infrastructure serves as a basic condition to attract foreign firms in an area. Cities with better infrastructure are most likely to attract higher FDI. Two measures of infrastructure are used as instruments: *length of national highways* and *availability of non-agricultural land*. The more non-agricultural land the state has, the easier it is for firms to establish their plants in that area.

The *fractionalization index* is used to take into account caste and religious heterogeneity in India. The larger the fractionalization, the lesser will be the chances of FDI inflow in a region. Foreign firms will search for safe and better environments to invest in a particular area. This information on states is also used to instrument for FDI.

4.2 Testing the instruments

Following the discussion on endogeneity, a suitable instrument for foreign share is determined from the available set of instruments. The Montiel–Pflueger test is used to check for robustness of instruments (Table 3). The instrument log of population is above the threshold value of 10.780, which suggests it can serve as a good instrument for foreign share. However, it drops to 6.572 when log of non-agricultural land is applied. Next, log of distance from the main market area is tested and the value is 10.953, above the threshold of 10. The value for log of national highways is 9.696, which is very close to the threshold in Table 3. The last instrument tested for is the fractionalization index. The value of the index (9.526) is also close to the threshold. Two different specifications are applied: one with all the instruments, and another with those above the threshold level. It also allows testing for the robustness of all coefficients. Besides using them separately in this study, the combination of these instruments was used while testing for both static and dynamic GMM.

5 Data

Annual reports of companies containing information on income statements and balance sheets are one of the most important sources of firm level data. This study uses the Prowess database, described as 'the largest and most comprehensive database on the financial performance of Indian business entities' (CMIE 2016). The database covers listed and unlisted large, medium, and small firms of the manufacturing and service sectors. It includes non-financial public and private limited manufacturing firms trading on the National Stock Exchange and the Bombay Stock Exchange. The present study uses unbalanced panel data for manufacturing firms from sectors including metal, chemicals, construction, consumer goods, food, machinery, textiles, and transport equipment for the period 2001–15, and identifies firms by the districts in which they operate.[6]

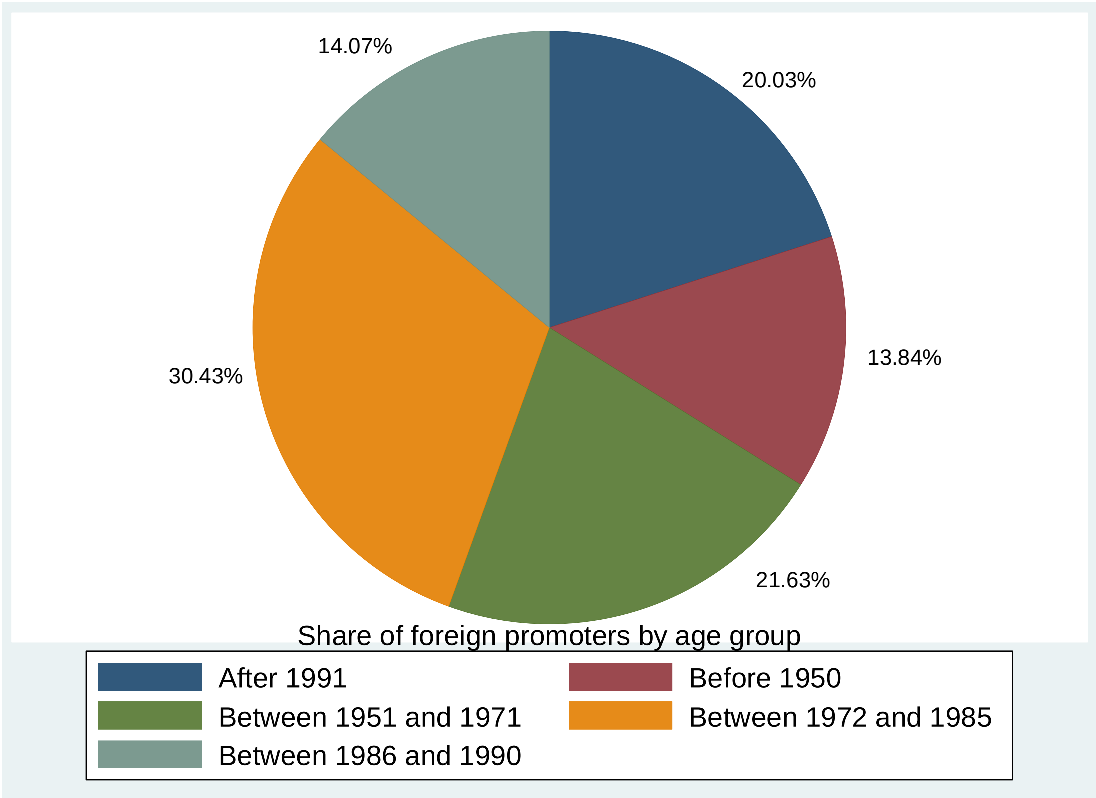
5.1 Distribution of foreign firms

The unbalanced panel includes firms from different age group categories. Figure 5 represents the distribution of foreign firms by age. The largest numbers of foreign firms (30.4 per cent) belong to the age group 43–30 years, followed by 64–44 years (21.59 per cent) and relatively new firms with fewer than 24 years of experience. Thus, more than 50 per cent of foreign firms belong to a relatively 'old' age group. Large part of the study sample includes firms from deciles 1–4. Figure 6 plots the size-wise distribution of foreign firms. The deciles are formed on the basis of three-year averages of summation of income and assets. Thus, it is based on the last three years' performance of a firm. Almost 70 per cent of Indian firms have been performing better since the last three years.

Figure 7 depicts the distribution of foreign firms across states in India. A large percentage of firms in the study sample (30.85 per cent) are from Maharashtra, followed by Gujarat and Andhra Pradesh (12.8 per cent in both) and Haryana (9.14 per cent). These figures are in line with the macroeconomic figures presented in Figure 2. These are also the states with better infrastructure and resources to attract foreign investors. Figure 8 shows the distribution of foreign firms across industries and is in line with Figure 1. Of the whole sample, 25.18 per cent of foreign firms are in the chemical sector, followed by 21.41 per cent in machinery and 11.6 per cent in the transport equipment or automobiles sector.

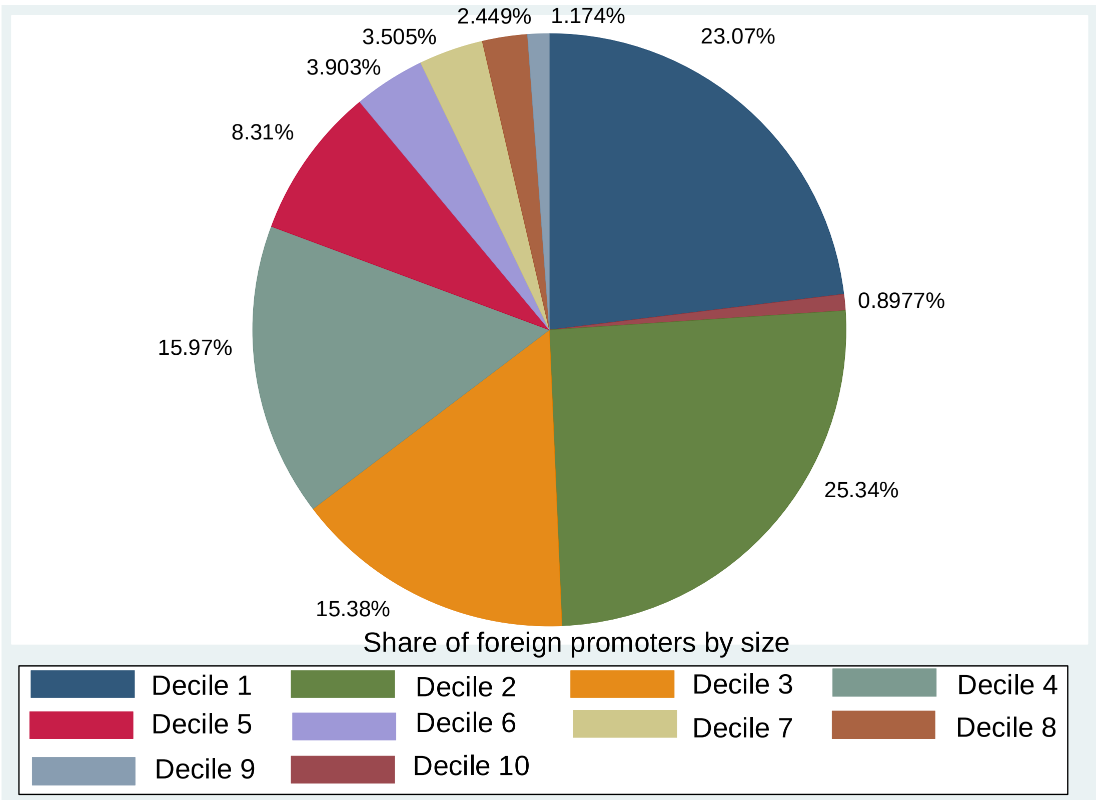
[6] I tested for attrition in data using an inverse probability method and found 19 per cent attrition, which I corrected by taking into account the weights in estimation. The results are robust to the exclusion of weights in estimation.

Figure 5: Distribution of foreign firms by age



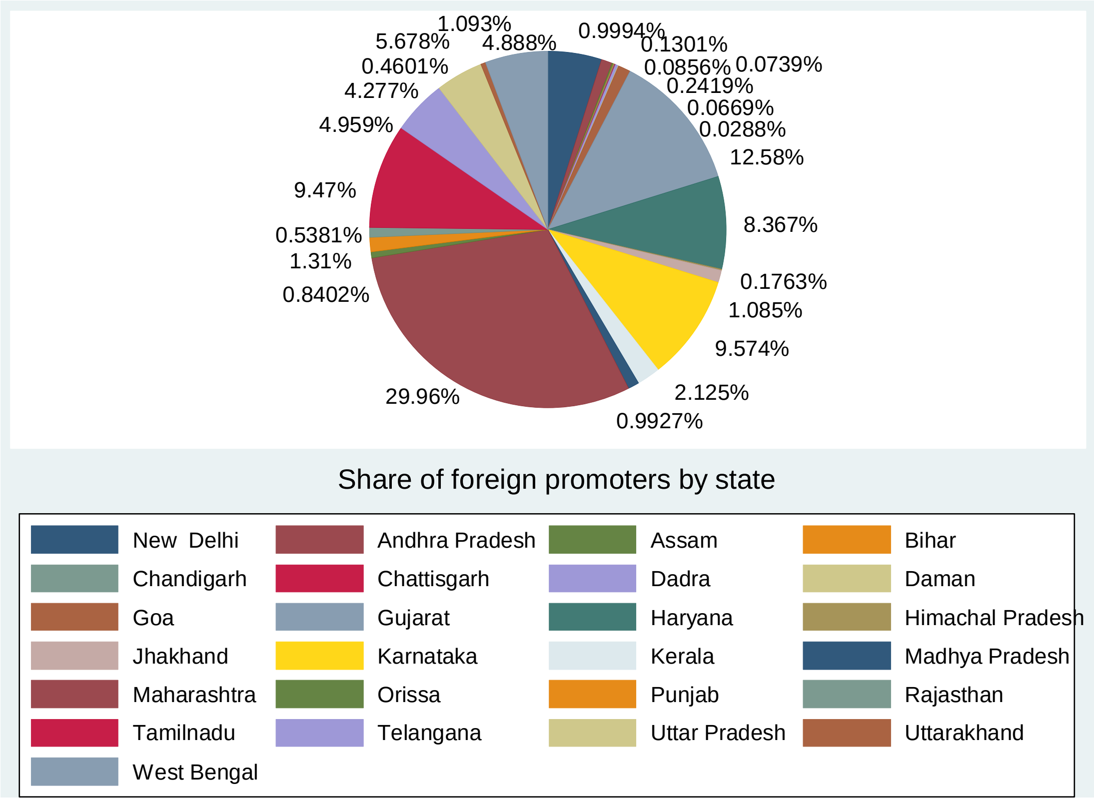
Source: Author's depiction based on calculations and data from the Prowess database (CMIE 2016).

Figure 6: Distribution of foreign firms by size



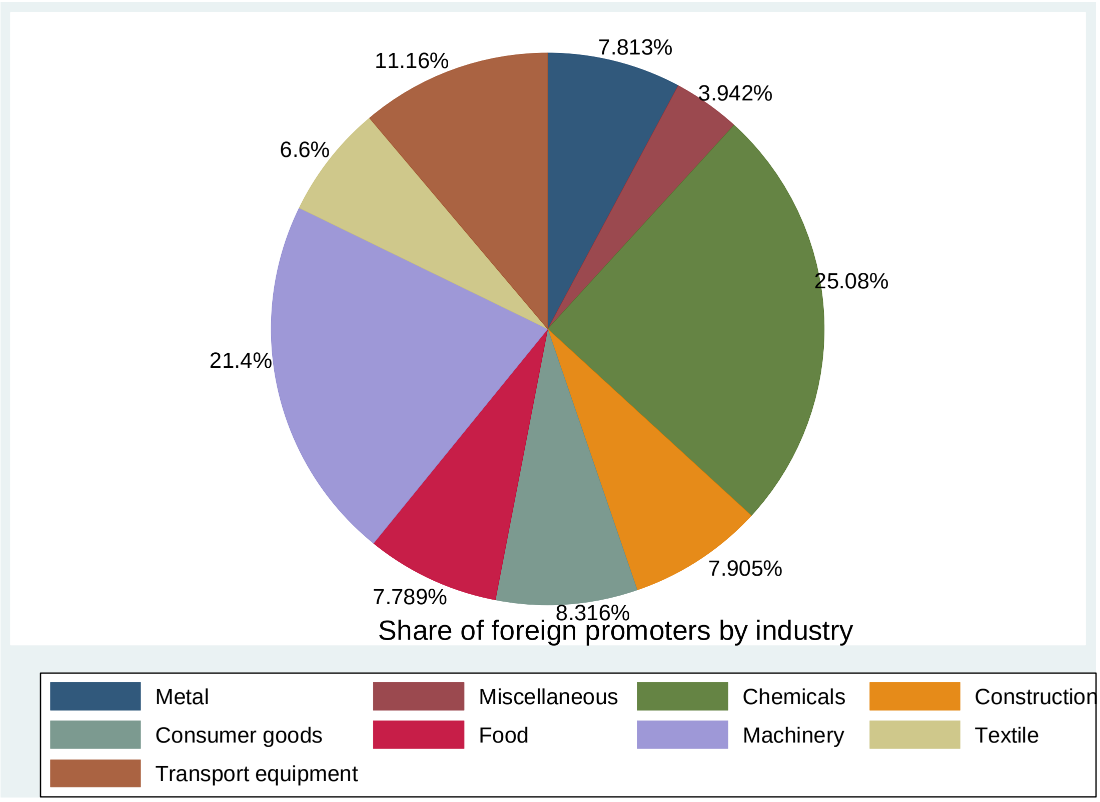
Source: Author's depiction based on calculations and data from the Prowess database (CMIE 2016).

Figure 7: State-wise distribution of foreign firms



Source: Author's depiction based on calculations and data from the Prowess database (CMIE 2016).

Figure 8: Industry-wise distribution of foreign firms



Source: Author's depiction based on calculations and data from the Prowess database (CMIE 2016).

6 Results and discussion

6.1 Static and dynamic GMM results

This study tested the static IV method first, followed by dynamic versions of the baseline model with different specifications. Two different types of relative wages are used as dependent variables: skilled to unskilled relative wages and industrial relative wages. The latter can also be interpreted as the average wages because it is a ratio of firm wages to industry level wages. The endogeneity of FDI is taken into account and the baseline model is tested with different state level instruments available for FDI. The results use log of population, distance from main market area, length of national highways, availability of non-agricultural land, and the fractionalization index as instruments for FDI.

Appendix Table A1 shows results for the static IV model for the baseline equation with all the instruments and rural relative wages as dependent variables. Positive and significant coefficient of the share of foreign firms in all the different model specifications is found to range from 0.36 for GMM to 0.72 for LIML. The coefficient of CUE is 0.45. So, 1 per cent increase in the share of foreign firms is associated with 0.36–0.72 point increase in relative wages based on static IV estimation. The coefficient of training is also positive and significant, as expected, in the CUE model (see column (5), Appendix Table A1). The main coefficient of interest is the interaction term *FDI×training*. All columns (2–5) in Appendix Table A1 with different model specifications show a positive and significant effect of the interaction term *FDI×training* on relative wages. This suggests the significance of demand side effect of human capital formation via on-the-job training by foreign firms. It implies that the demand for skilled workers is more dominant than the supply of skilled workers by foreign firms via on-the-job training. On the basis of the instrument testing, the three most significant instruments are chosen and tested for a combination of log of population, distance from main market area, and fractionalization on FDI (Appendix Table A2). The results remain robust for all the different specifications (2SLS, GMM, LIML, IV, ExIV2SLS, and CUE) (see columns (1)–(5), Appendix Table A2). The results depict a positive coefficient of β_3; that is, interaction term *FDI×training* ranging from 0.001 to 0.0008, which confirms the previous results. The value of the Kleibergen–Paap *rk* language multiplier (LM) statistic is also above the threshold level in Ex2SLS and CUE estimations (columns (4) and (5), respectively, Appendix Table A2. The results remain the same when industrial relative wages is regarded as a dependent variable (Appendix Table A3). The coefficient of foreign share now ranges from 0.17 to 0.27 with significance at 5 per cent. However, on-the-job training becomes insignificant. The coefficient of interaction term also remains positive and significant, ranging from 0.001 to 0.0002 indicating validity of the previous results. The coefficient of industrial wages as a dependent variable ranges from 0.001 to 0.009, whereas for foreign share it increases to 0.46 when only log of population, distance from main market area, and fractionalization are considered (Appendix Table A4). Interaction term remains significant and positive for all the different models.

Appendix Table A5 shows results of applying dynamic GMM with all instruments and the set of significant instruments. Column (1) shows the results for rural wages as the dependent variable along with all the instruments used for foreign share. The coefficient of foreign share drops to 0.20 but remains positive and significant. Taking into account the endogeneity of the system does not affect the interaction term, which remains positive and significant in this model. The Sargan *P* value of 0.93 and Hansen value of 0.38 confirm the validity of previous results. The effect remains the same with the robust set of instruments (column (2)), with the coefficient of foreign share dropping to 0.19 and training becoming positive and significant with a value of 2.42. The coefficient of foreign share and training expenses remains the same. The exercise is repeated for industrial wages as the dependent variable with and without all instruments (in columns (3) and (4), respectively). The interaction term remains positive and significant, although foreign share and training remain positive but become insignificant.

6.2 Review of results: A discussion

This section compares the present study with the existing literature on the effect of FDI on host countries. The existing literature on the supply side effects of FDI on a host country's labour market is still at a nascent stage. This study takes into account the demand and supply effects of FDI and endogenizes decision-making on the part of foreign firms to enter into a host country using external instrument. Results confirm the existence of a positive demand side effect of FDI on the labour market by raising wage inequality in a host country. These results seem to be in line with the previous literature. Among other studies on the effect of a firm's expenses on the labour market, Tan and Batra (1997) examine the effect of a firm's 'technology-generating' expenses on wage inequality for Columbia, Mexico, and Taiwan using a cross-section of manufacturing sector firms. Using semi-parametric estimation techniques, they find positive relationship between skilled wages and different firm level characteristics, thus supporting the skill demand hypothesis by firms. They find the effects of research and development (R&D) and training stronger than that of exports. Ballot et al. (2006), using dynamic panel data methods for French and Swedish firms, find that foreign firms do not distribute the share of labour to workers specifically for R&D and training investments. The investments in intangible assets are captured better by foreign firms. Baranwal (2016) finds a positive effect of FDI on the demand for high-skilled workers compared with mid- and low-skilled workers, although with a different dataset. Some studies in India find a positive effect of the liberalization process on wage inequality. For example, Chamarbagwala (2006), using a non-parametric methodology specifically by trade and outsourcing, finds increasing within-industry wage inequality biased in favour of skilled labourers. Hasan et al. (2007) also find a positive effect of trade on demand elasticity of labour in the Indian manufacturing sector, and a declined overall share of labour in total output. Azam (2010) finds tertiary and secondary wage premium increasing for the period 1983–2005 owing to reduction in supply of labour for this period. In contrast, using panel data on Venezuelan firms, Aitken and Harrison (1999) find a negative effect of foreign firms on indigenous firms, but they mostly use ordinary least-squares technique for estimation. Fu and Gong (2011) test for a panel of Chinese firms and find high-technology indigenous firms contribute to technological upgradation, whereas innovation practices of foreign firms affect domestic technical change in indigenous firms. They use the system GMM technique with lagged values of endogenous variables as instruments. Using internal instruments or the lagged value of endogenous regressors as instrument may not give the unbiased results owing to correlation between the actual and lagged values of regressors. However, using external instruments checks for possible endogeneity and improves the credibility of results. The literature on productivity spillovers estimation by foreign firms also pictures the lack of indirect spillovers by foreign firms in indigenous firms, as earlier discussed. The validity of results is also confirmed by choosing different estimation strategies. For the static IV regression, 2SLS, extended 2SLS, and GMM are used as also LIML and CUE specifications of the model. Standard errors are consistent under homoscedasticity for both these estimators, thus reducing the biasedness of coefficients. Similarly, the choice of different instruments allows checking for different combinations of instruments and the validity of results, confirmed by different combinations of instruments. Using system GMM allows checking for possible endogeneity that may have caused biased coefficients. The robustness of results from a dynamic setting supports the validity of results. In fact, the heterogeneity at different levels also supports the increases in wage inequality caused by foreign firms. The effect is consistent for all sizes of firms and for older firms and regions. High-technology firms have a high effect of foreign share on wages as well as the interaction term, which is quite expected via the channel of training.

6.3 Heterogeneity and other robustness checks

Heterogeneity is explored at different levels in the present study dataset. Different levels of heterogeneity are tested in the data for static GMM using all instruments.

Results from the size group remain robust to previous regressions. Appendix Table A6 shows the results for firms belonging to different deciles. Decile 1 firms have the highest positive coefficient of 0.48 compared with firms in deciles 2 and 3, which have coefficients of 0.32 and 0.19, respectively. The coefficient of interaction term *foreign share*×*training* is also positive for all deciles, but is significant for firms in deciles 1 and 3.

Appendix Table A7 shows the results for the baseline model for different age groups of firms. Positive and significant coefficient of foreign share is noted for firms belonging to the age groups >65 and 43–30 years. The interaction term is also positive and significant for firms in the age group >65 years and 29–25 years. Thus, relatively older and middle-aged firms have higher demand side effect of foreign share on relative wages.

Industry-wise results are depicted in Appendix Table A8. Firms in high- and low-technology industries are tested for separately: the former category includes metal, chemicals, machinery, and transport equipment firms, and the latter includes food, textiles, consumer goods, and construction. Results suggest that the high-technology firms show a positive and significant coefficient of foreign share (0.61). The coefficient of interaction term also remains positive and significant. However, no significant results are found for low-technology firms.

Appendix Table A9 shows the results for different regions. The states are divided into four regions: north, south, east, and west. Results show the positive effect of the interaction term in all the regions, although the effect of foreign share and training is not significant.

In further analysis, the baseline model is tested with balanced panel and results are shown in Appendix Table A10. They suggest the coefficient of foreign share remains in a similar range (0.40–0.49) as static results. The coefficient of training is also positive and significant, ranging from 2.34 to 4.70 for different specifications of the models. Interestingly, the coefficient of interaction term also remains positive and significant confirming prior results.

The changes in Indian shares in firms are examined and the robustness of results is reported in Appendix Table A11. The results reveal a significant and positive coefficient of 0.67 for foreign share, suggesting a positive effect of foreign share on relative wages; this is confirmed by the interaction term *foreign share*×*training*. Thus, given the shares of Indian promoters in Indian firms the hypothesis of increasing wage inequality by foreign firms remains robust.

Following the literature on impact of FDI on host countries, another channel of effect of foreign share on wage inequality is explored and results are reported in Appendix Table A12. R&D expenses of firms are taken into account. These expenses may create knowledge spillovers in the host economy, correlate with demand for skilled labour, and affect wages through this channel. No significant effects of R&D and its interaction term are found. However, the effect of foreign share and the interaction term *foreign share*×*training* are still positive and significant.

The variation in investment by firms in the study dataset is exploited by dividing the dataset into high- and low-investment groups by the median value of investment (Appendix Table A13). The results suggest a positive effect of foreign share on relative wages in high-investment firms along with a positive coefficient of interaction term *foreign share*×*training*, suggesting a positive relative demand effect. The effect of foreign share for low-investment firms is in the same direction as that of high-investment firms, although with a smaller magnitude. The interaction term is positive but not significant.

7 Conclusion

The high inflows of FDI in the Indian economy, with reduction and removal of sectoral caps in many sectors in the post-reform period (especially after 2000), provides a good background to probe into the labour market effects. Although the literature accounts for the indirect effects of FDI in host countries by different horizontal and vertical spillover channels, there is still dearth of literature on assessing this effect with the direct channel of on-the-job training specifically in India. This paper attempts to examine whether FDI has helped the Indian manufacturing sector in the period 2001–15. The paper takes into account the dynamics involved in the process and uses static and dynamic GMM to test FDI effects. It also considers decision-making on the part of foreign firms to invest as endogenous.

This study uses different tested instruments that determine FDI, including market size, infrastructure, distance from main market area, and a religion and cast fractionalization index. All these instruments have been tested properly and used by previous studies. It checks the robustness of the results by using more efficient and different methods of static GMM, and different combinations of more significant instruments.

The study fails to find any positive human capital formation effects through on-the-job training given to employees. Rather, it finds a positive demand side effect of foreign firms-led human capital formation; that is, the increase in wage inequality over time. The results also remain robust with different alterations of the models and while accounting for different levels of heterogeneity, for example: different high- and low-technology industries, age-wise, size-wise, controlling for R&D, and Indian shares of firms. Another robustness check divided the industries on the basis of investment; the results remain robust.

Regarding the policies on effect of FDI on human capital formation in host countries, there are examples of better coordination between government and MNEs to lessen the demand and supply gap in the labour market, such as Singapore's Skill Development Fund, Malaysia's Human Resource Development Fund, and the Penang Skill Development Centre; they represent coordination between government, business, and academia in supplying skills. Although India has started the National Skill Development Corporation, which aims to create skills by establishing vocational institutes using public–private partnerships, empirical evidence suggests that there is requirement for better coordination between institutions to bridge the skill gap that may have caused these results.

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Appendix A: Definitions and static–dynamic results

A1 Definition of variables

- $\{rlw\}_{it} = \{w_{Sit} / w_{Uit}\}$: relative price of labour, ratio of skilled and unskilled labour force in firms.
- FS_{it}: equity shares held by foreign promoters in the firm.
- $train_{it}$: annual on-the-job training expenses of firms.
- $size_{it}$: annual sales of the firms.
- $FS_{it} \times train_{it}$: interaction term of equity shares and training expenses of firms.

A2 Definition of instruments (state-wise)

- *Size of main market*: log of population.
- *Distance from main market area*: log of distance from main market area in kilometres.
- *Length of national highways*: log of length of national highways in kilometres.
- *Availability of non-agricultural land*: log of available non-agricultural land.
- *Fractionalization index* (*FI*) = $\sum_{g=1}^{n} q_{gi}^{2}$, where g is population share of caste or religious group.
- *Foreign direct investment* (*FDI*): proxy for measuring FDI is foreign equity in annual equity shares of firms. It is a continuous variable ranging from 0 to 100.
- *On-the-job training*: measure of annual expenses financed by firms on training their employees (which upgrades the level of skills). This term is normalized by dividing it by sales of firms.
- FDI_{train}: interaction term of foreign equity shares and on-the-job training expenses of firms.
- *Size*: total annual sales of the firms; it controls for firm-specific characteristics.
- *Size*^{2}: term that accounts for the non-linarites in firm-specific indicators.

Table A1: Static IV results, relative wages (rural) dependent variable (*all instruments*)

Explanatory variables	2SLS (1)	GMM (2)	LIML (3)	ExIV2SLS (4)	CUE (5)
Foreign share	0.41** (0.12)	0.36** (0.11)	0.72** (0.20)	0.41** (0.12)	0.45*** (0.11)
Training	0.02 (0.01)	0.01 (0.01)	0.03 (0.01)	0.02 (0.01)	0.01*** (0.01)
Foreign share×Training	0.001*** (0.00001)	0.001*** (0.0001)	0.0009*** (0.00001)	0.001*** (0.0001)	0.001*** (0.0001)
Size	0.003*** (0.00005)	0.0003*** (0.0004)	0.0008 (0.00005)	0.0003*** (0.0005)	0.0003*** (0.00005)
Size^2	–3.85e–09 (4.66e–100)	–3.54e–09*** (4.25e–10)	—	–3.85e–09*** (4.66e–10)	–3.60e–09*** (4.38e–10)
R^2	0.64	0.66	0.33	0.72	0.66
Montiel–Pflueger robust weak instrument test	7.332	7.332	7.399	—	—
Kleibergen–Paap *rk* LM statistic				34.818	34.818
Cragg–Donald Wald *F* statistic				5.946	5.946
Kleibergen-Paap *rk* Wald F statistic				7.762	7.762
Constant	–26.11*** (7.22)	–23.07*** (6.56)	–43.53*** (12.08)	–26.11*** (7.22)	–28.83*** (7.08)
N	1376	1376	1376	1376	1376

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.

Table A2: Static IV results, relative wages (rural) dependent variable (*log of population + distance from main market area + fractionalization)*

Explanatory variables	2SLS (1)	GMM (2)	LIML (3)	ExIV2SLS (4)	CUE (5)
Foreign share	0.85** (0.25)	0.75** (0.21)	0.92** (0.28)	0.85** (0.25)	0.85** (0.23)
Training	0.04* (0.02)	0.03 (0.02)	0.05* (0.02)	0.04* (0.02)	0.04* (0.02)
Foreign share×Training	0.0008*** (0.00001)	0.0009*** (0.00001)	0.0008*** (0.0001)	0.0008*** (0.00001)	0.001*** (0.0004)
Size	0.0001*** (0.00006)	0.0001*** (0.00006)	0.0001* (0.00002)	0.0001*** (0.00006)	0.0008*** (0.0001)
Size^2	4.36e–11 (1.94e–10)	5.98e–11 (1.96e–10)	—	4.36e–11 (1.94e–10)	–4.67e–11*** (1.97e–10)
R^2	0.65	0.43	0.48	0.65	0.41
Montiel–Pflueger robust weak instrument test	7.264	7.281	7.264		
Kleibergen–Paap *rk* LM statistic				19.731	19.731
Cragg–Donald Wald *F* statistic				4.800	4.800
Kleibergen–Paap *rk* Wald *F* statistic				8.26	8.26
Constant	–44.61** (12.82)	–44.61** (12.82)	–54.85** (16.63)	–51.05** (14.83)	–50.68*** (13.81)
N	1608	1608	1608	1608	1608

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.

Table A3: Static IV results, relative wages (industrial) dependent variable (*all instruments*)

Explanatory variables	2SLS (1)	GMM (2)	LIML (3)	ExIV2SLS (4)	CUE (5)
Foreign share	0.27** (0.11)	0.27** (0.08)	0.17 (0.11)	0.27** (0.18)	0.25** (0.09)
Training	–0.008 (0.01)	–0.01 (0.01)	–0.02 (0.01)	–0.008 (0.01)	–0.01 (0.01)
Foreign share×Training	0.0002** (0.00007)	0.001*** (0.0004)	0.003*** (0.0008)	0.0002** (0.00007)	0.0002*** (0.00007)
Size	0.0001*** (0.00001)	0.0001*** (0.00001)	0.0004** (0.00001)	0.0001*** (0.00001)	0.001*** (0.0001)
Size^2	–1.67e–10** (2.59e–11)	–1.57e–10*** (2.43e–11)	—	–1.67e–10** (2.59e–11)	–1.59e–10*** (2.45e–11)
R^2	0.61	0.62	0.54	0.66	0.53
Montiel–Pflueger robust weak instrument test	8.808	8.808	8.829		
Kleibergen–Paap *rk* LM statistic				39.811	39.811
Cragg–Donald Wald *F* statistic				6.890	6.890
Kleibergen–Paap *rk* Wald *F* statistic				8.405	8.405
Constant	–14.56* (6.46)	–11.18 (5.25)	–8.16 (6.83)	–14.56* (6.46)	–13.34** (5.44)
N	1788	1788	1788	1788	1788

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author’s compilation based on study dataset.

Table A4: Static IV results, relative wages (industrial) dependent variable (*log of population* + *distance from main market area* + *fractionalization*)

Explanatory variables	2SLS (1)	GMM (2)	LIML (3)	ExIV2SLS (4)	CUE (5)
Foreign share	0.43** (0.18)	0.41** (0.18)	0.43** (0.23)	0.43** (0.18)	0.46** (0.18)
Training	-0.007 (0.01)	0.005 (0.01)	0.002* (0.01)	0.007 (0.01)	0.009 (0.01)
Foreign share×Training	0.0001** (0.00001)	0.002*** (0.0006)	0.0004*** (0.0001)	0.0002** (0.00007)	0.0002*** (0.00006)
Size	0.0001*** (0.00001)	0.0001*** (0.00001)	0.0003** (0.00007)	0.0001*** (0.00002)	0.001*** (0.0001)
Size^2	–1.59e–10** (2.35e–11)	–1.57e–10*** (2.33e–11)	—	–1.59e–10** (2.35e–11)	–1.60e–10*** (2.35e–11)
R^2	0.51	0.52	0.43	0.61	0.53
Montiel–Pflueger robust weak instrument test	6.213	6.83	6.244		
Kleibergen–Paap *rk* LM statistic				20.808	20.808
Cragg–Donald Wald *F* statistic				4.133	4.133
Kleibergen–Paap *rk* Wald *F* statistic				7.543	7.543
Constant	–23.38* (10.68)	–22.19 (10.44)	–23.00* (13.43)	–23.38* (10.68)	–25.32* (10.83)
N	2096	2096	2096	2096	2096

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author’s compilation based on study dataset.

Table A5: Dynamic system GMM results, relative wages (rural and industrial) dependent variable

Explanatory variables	(1)[a1] (*all*) Rural wages	(2)[b1] (*population* + *distance* + *fractionalization*) Rural wages	(3)[a1] (*all*) Industrial wages	(4)[b1] (*population* + *distance* + *fractionalization*) Industrial wages
Relative wages	0.92* (0.42)	0.95* (0.24)	1.13*** (0.16)	1.50*** (0.33)
Foreign share	0.20*** (0.04)	0.19*** (0.0)	0.03 (0.02)	0.001 (0.008)
Training	−1.37 (0.59)	2.42*** (0.60)	1.56 (0.94)	0.84 (0.64)
Foreign share×Training	0.0003** (0.0001)	0.0003** (0.0001)	0.0003** (0.0001)	0.0008** (0.0004)
Size	0.0003 (0.00002)	0.0002 (0.0002)	0.0003 (0.0007)	0.0007 (0.0007)
AR (1)	−1.82 (0.06)	−1.82 (0.06)	−1.70 (0.08)	−1.80 (0.07)
AR (2)	−1.14 (0.25)	−1.14 (0.25)	−1.29 (0.29)	0.39 (0.69)
Sargan test (*P* value)	(0.93)	(0.93)	(0.85)	(0.59)
Hansen test (*P* value)	(0.38)	(0.38)	(0.79)	(0.80)
Instruments	54	51	31	29
N	867	867	993	999

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.

Table A6: Static IV results, relative wages (rural) dependent variable (*all instruments*), size-wise heterogeneity

Explanatory variables	Decile 1 (1)	Decile 2 (2)	Decile 3 (3)
Foreign share	0.48** (0.18)	0.32* (0.19)	0.19** (0.08)
Training	0.01 (0.03)	5.27* (3.63)	5.47 (8.51)
Foreign share×Training	0.001*** (0.0002)	0.0004 (0.0008)	0.002*** (0.001)
Size	0.0004*** (0.00008)	0.002*** (0.0009)	0.0003** (0.0001)
Size^2	–4.63e–09*** (5.71e–10)	2.58e–11** (2.40e–10)	6.12e–09*** (1.39e–08)
R^2	0.73	0.84	0.78
Constant	–31.23*** (11.38)	–18.52* (10.64)	–10.97** (4.56)
Kleibergen–Paap *rk* LM statistic	24.003	6.945	12.223
Cragg–Donald Wald *F* statistic	6.665	1.388	5.233
Kleibergen–Paap *rk* Wald *F* statistic	7.963	3.198	7.966
N	762	620	226

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.

Table A7: Static IV results, relative wages (rural) dependent variable (*all instruments*), age-wise heterogeneity

Explanatory variables	>65 years (1)	65–44 years (2)	43–30 years (3)	29–25 years (4)	<24 years (5)
Foreign share	0.30*** (0.10)	–0.06 (0.24)	0.01* (0.006)	0.09 (0.06)	–0.03 (0.09)
Training	1.61 (2.37)	–3.61 (1.52)	0.005* (0.002)	0.008 (0.009)	59.21 (26.07)
Foreign share×Training	0.001*** (0.0001)	0.001*** (0.0002)	0.0001 (0.0002)	0.006*** (0.0001)	0.008 (0.003)
Size	0.003*** (0.0005)	0.0002*** (0.0007)	0.0005 (0.0006)	0.0006*** (0.00005)	0.0006*** (0.0001)
Size^2	–6.80e–09*** (1.23e–09)	–4.55e–09*** (8.76e–10)	–1.46e–08** (4.68e–09)	–2.20e–08 (3.63e–09)	–8.36e–09*** (2.01e–09)
Constant	–0.41 (6.05)	–16.02** (5.47)	0.87 (14.72)	–9.56 (5.98)	–0.415 (6.05)
Kleibergen–Paap *rk* LM statistic	11.556	13.969	10.228	25.560	11.252
Cragg–Donald Wald *F* statistic	5.202	2.495	2.427	8.612	1.524
Kleibergen–Paap *rk* Wald *F* statistic	4.753	3.773	2.46	15.152	3.776
N	317	538	191	230	205

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.

Table A8: Static IV results, relative wages (rural) dependent variable (*all instruments*), industry-wise heterogeneity

Industries	*Foreign share*	*Training*	*Foreign share×Training*	*Size*	*Size*^{2}	Kleibergen–Paap *rk* LM statistic	Cragg–Donald Wald *F* statistic	Kleibergen–Paap *rk* Wald *F* statistic	*N*
High-technology industries (chemicals, metal, machinery and transport equipment)	0.61*** (0.20)	–2.01 (1.64)	0.009*** (0.0002)	0.001*** (0.0001)	–1.94e–11*** (3.60e–10)	25.310	6.282	10.439	1163
Low-technology industries (food, textiles, construction and consumer goods)	***0.16 (0.12)***	***0.003 (0.001)***	0.0003 (0.0002)	0.004*** (0.006)	–6.42e–09*** (1.21e–09)	9.964	2.200	4.855	445

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.

Table A9: Static IV results, relative wages (rural) dependent variable (*all instruments*), state-wise heterogeneity

States	*Foreign share*	*Training*	*Foreign share×Training*	*Size*	*Size*^{2}	Kleibergen–Paap *rk* LM statistic	Cragg–Donald Wald *F* statistic	Kleibergen–Paap *rk* Wald *F* statistic	*N*
North	0.26 (0.20)	−0.53 (0.38)	0.001** (0.007)	0.0001** (0.00001)	−1.49e−10*** (2.90e−11)	14.083	3.503	5.131	434
South	0.04 (0.09)	22.83* (12.40)	0.001** (0.005)	0.0005** (0.0008)	−5.64e−09*** (1.42e−08)	8.115	4.028	4.279	369
East	0.04 (0.04)	0.35 (3.25)	0.001*** (0.0006)	0.006** (0.0001)	−1.40e−08*** (6.68e−09)	8.970	4.788	10.125	176
West	0.07 (0.13)	0.001 (0.01)	0.003* (0.002)	0.0003* (0.00007)	−3.39e−10*** (2.34e−10)	9.350	3.828	6.552	771

Note: 'North' includes New Delhi, Bihar, Chandigarh, Haryana, Himachal Pradesh, Punjab, Uttar Pradesh, and Uttarakhand; 'South' includes Andhra Pradesh, Karnataka, Kerala, Tamilandu, Telangana, and Pondicherry; 'East' includes Assam, West Bengal, and Orissa. 'West' includes Gujarat, Maharashtra, Rajasthan, Dadra and Nagar Haveli, Daman and Diu, and Goa. Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.

Table A10: Static IV results, relative wages (rural) dependent variable (*all instruments*), balanced panel results

Explanatory variables	2SLS (1)	GMM (2)	LIML (3)	ExIV2SLS (4)	CUE (5)
Foreign share	0.44*** (0.09)	0.41*** (0.08)	0.48** (0.15)	0.40*** (0.09)	0.49*** (0.10)
Training	3.89* (2.55)	3.53* (2.39)	2.34 (4.96)	3.05 (2.48)	4.70** (2.65)
Foreign share×Training	0.0009*** (0.00001)	0.001*** (0.0001)	0.001*** (0.00008)	0.009*** (0.0001)	0.0009*** (0.0001)
Size	0.003*** (0.00005)	0.0001*** (0.0004)	0.001*** (0.00001)	0.0002*** (0.0004)	0.0001*** (0.00004)
Size^2	−3.91e−09*** (1.05e−09)	−3.83e−09*** (1.01e−09)	—	−4.02e−09*** (1.07e−09)	−3.60e−09*** (1.09e−09)
R^2	0.40	0.44	0.30	0.60	0.49
Montiel–Pflueger robust weak instrument test	5.518	5.518	4.043	—	—
Kleibergen–Paap *rk* LM statistic				23.277	23.277
Cragg–Donald Wald *F* statistic				4.307	4.307
Kleibergen–Paap *rk* Wald F statistic				5.007	5.007
Constant	−22.32*** (4.91)	−20.91*** (4.47)	−24.02** (8.02)	−20.67*** (4.84)	−25.5158 (5.35)
N	503	503	503	503	503

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.

Table A11: Static IV results, relative wages (rural) dependent variable (*all instruments*), controlling for Indian shares

Explanatory variables	(1)
Foreign share	0.67*** (0.17)
Training	0.03** (0.01)
Foreign share×Training	0.001*** (0.0002)
Indian share	0.03* (0.01)
Size	–0.006*** (0.00006)
$Size^2$	–9.58e–09*** (2.01e–09)
R^2	0.55
Kleibergen–Paap *rk* LM statistic	22.089
Cragg–Donald Wald *F* statistic	3.825
Kleibergen–Paap *rk* Wald F statistic	4.797
Constant	–37.4716*** (9.32)
N	1145

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.

Table A12: Static IV results relative wages (rural) dependent variable controlling for R&D expenses.

Explanatory variables	(1)
Foreign share	0.73** (0.27)
Training	186.69 (50.09)
Foreign share×Training	0.0008** (0.0003)
Indian share	0.04 (0.03)
R&D expenses	–5.38 (9.96)
Foreign share×R&D expenses	–0.13 (0.25)
Size	0.0001*** (0.0004)
$Size^2$	–3.83e–09*** (1.01e–09)
Constant R^2	0.76
Kleibergen–Paap *rk* LM statistic	11.745
Cragg–Donald Wald *F* statistic	1.902
Kleibergen–Paap *rk* Wald F statistic	2.388
Constant	–44.66** (14.09)
N	369

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.

Table A13: Static IV results relative wages (rural) dependent variable (investment-wise)

Explanatory variables	High investment (1)	Low investment (2)
Foreign share	0.98* (0.67)	0.18** (0.06)
Training	–1.70 (1.55)	30.77** (12.22)
Foreign share×Training	0.0008*** (0.0002)	0.0003 (0.0004)
Size	0.0001 (0.0008)	0.0003** (0.0004)
$Size^2$	1.69e–10 (2.50e–10)	6.73e–09 (1.48e–08)
Constant	–62.66** (40.03)	–12.12** (4.00)
R^2	0.61	0.50
Kleibergen-Paap rk LM statistic	4.427	25.000
Cragg-Donald Wald F statistic	1.456	7.224
Kleibergen-Paap rk Wald F statistic	1.537	8.840
N	549	490

Note: Robust standard errors are in parentheses. All specifications include full set of time and two-digit level industry dummies. *, **, and *** indicate levels of significance at 10, 5, and 1 per cent.

Source: Author's compilation based on study dataset.