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The Effect of China's New Labor Contract Law on Human Capital Investment of Migrant Workers' Families

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Abstract: We take the implementation of "China’s New Labor Contract Law" (NLCL) in 2008 as a quasi-natural experiment, and apply the Difference-in-Differences method to assess the impact of the policy on human capital investment in migrant workers’ families. Our analysis reveals that the NLCL leads to a significant increase in education expenditure among migrant workers’ families. Heterogeneity analysis shows that the effect is more pronounced in families with higher education levels, families with only one child, and families that belong to medium income levels. Mechanism analysis suggests that the NLCL increases the likelihood of migrant workers receiving pension and medical insurance, thereby reducing the associated risks and burdens for families and ultimately boosting education spending. The NLCL not only protects the labor rights and interests of vulnerable groups like migrant workers, but also has significant implications for enhancing human capital investments, promoting social mobility, and achieving shared prosperity.

Key words： migrant workers; New Labor Contract Law; human capital investment

I. Introduction

Education is one of the most important human capital for families. It not only boosts the occupational status and income of disadvantaged groups, but also enables upward mobility among children from disadvantaged families (Liu & Yuan, 2021; Guo & Min, 2007). However, the paths to upward mobility are narrowing in China, particularly for children from low-income families such as migrant workers (Guo et al.,2019). These families often receive lower returns on education due to their lower educational attainment, which hinders their ability and willingness to invest in their own human capital and their children's education (Tan et al., 2017). Over time, this lack of motivation to seek upward mobility through education can lead to social instability and hinder economic development. Therefore, it is a very important research topic to explore how to improve the level of human capital investment of families, especially the disadvantaged families.

Migrant workers play a vital role in China's labor market, with a total of 295.6 million in this group by 2022[1]. However, migrant workers are often in a socially disadvantaged position, and they often face legal rights infringements and lack of social insurance coverage (Wong et al., 2007). In order to solve these issues, the New Labor Contract Law (NLCL) was implemented in 2008 to strengthen workers' protection and stabilize labor relations. The new law imposes strict restrictions on the signing, performance, suspension, and termination of labor contracts. It has been regarded as the most important reform of China's employment-related laws in over a decade (Cooney et al, 2007). This law has significantly affected the protection of workers' rights, especially for migrant workers, and has also influenced their household economic decisions. It is noteworthy that the NLCL significantly increases workers' household resource endowment in income and social insurance (Gao et al., 2012; Cheng et al., 2015; Qu, 2017). In terms of income, the law stipulates that employers must pay labor remuneration in full and the amount should not be lower than the local minimum wage. Otherwise, workers can terminate their employment contracts[2]. In terms of social insurance, the law not only requires that social insurance to be included as a mandatory clause in employment contracts, but also grants the government the right to inspect the payment of social insurance contributions by employers[3]. Under these impacts, migrant-worker households will have access to more economic resources for human capital investment, but this issue has not been rigorously analyzed empirically.

Considering these, this article has done beneficial exploration in this aspect. Our study reveals that the NLCL does increase the household education expenditure of migrant workers, and this result is robust and consistent across different tests. Furthermore, the heterogeneity analysis shows that the NLCL has a greater impact on education expenditure among migrant-worker households with higher levels of education and only one child. This effect is mainly concentrated in middle-income households, while it is not significant among low-income and higher-income households. Finally, we also find that the increased probability of access to pension and health insurance is an essential channel through which the NLCL increases the education expenditure of migrant-worker households. As a result, the NLCL encourages migrant workers to invest more in their children's education, thus contributing to the intergenerational mobility of education and the ultimate goal of common prosperity.

The research contributions of this paper are mainly shown in the following three aspects.

[1] Data from NSO's Migrant Worker Monitoring Survey Report 2022 http://www.gov.cn/lianbo/2023-04/28/content_5753682.htm

[2] Articles 85 and 38 of the Labour Contract Law.

[3] Articles 17 and 74 of the Labour Contract Law.

Firstly, we take the implementation of the NLCL in 2008 as a quasi-natural experiment, and examine its impact on the household human capital investment of migrant workers using the DID method for the first time. Secondly, we explore the mechanism of how the NLCL affects household human capital investment, focusing on pension insurance, social insurance, and risk aversion. This forms a logical analytical framework of "labor law, rights and interests protection, household decision-making". Thirdly, unlike existing literature, which focuses on changes in workers' welfare, we analyze the impact of labor protection policies on the human capital investment in the next generation, enriching research on policy evaluation from the perspective of human capital investment and social mobility.

The following parts of this paper are structured as follows: Part II summarizes the review of relevant literature; Part III introduces the data sources, the setting of the model and the selection of the sample; Part IV discusses the regression results of the impact of the NLCL on the education expenditure of migrant-worker families; Part V provides the results of heterogeneity analysis and mechanism exploration; Part VI concludes the whole paper.

II. Review of the literature

The impact of labor protection law on enterprises is the focus of academic research. From the perspective of labor protection law to enterprise management, researchers find that labor protection increases the dismissal cost of enterprises (Oi, 1962). Also, it increases the cost stickiness (Martinsetal., 2009; Wiel, 2010), which resulting in efficiency loss (Bradley et al., 2017). Lazear (1990) finds that labor protection law reduces the level of social employment, thus affects the value of enterprise (Lee and mas, 2012). But, Bena & Simintzi (2017)、Acharya et al. (2014) find that labor protection law encourages the technological innovation of enterprises, so as to reduce the cost of labors, ultimately improve enterprise performance and promoting economic growth. From the perspective of labor protection law on employment, it finds that labor protection law reduces the possibility of layoffs (Almeida & Carneiro, 2005). Basley & Burgess (2004) finds that the implementation of labor protection law reduces labor productivity by investigating the labor market in India. What's more, labor protection law can not only alleviate the negative effect of job instability on workers, but also be conducive to improving the quantity and quality of employment in the long run (Almeida & Aterido, 2011; Bjuggren, 2018). Based on the study of Mexico, Gutierrez (2014) finds that formal labor contracts are an important mechanism for workers to resist wage and income fluctuations caused by health shocks, and help workers better smooth their income and consumption. In addition, labor protection law has a positive spillover effect on the human capital development of workers' children (Ruiz-Valenzuela, 2020). . .

As for China, studies on the China's labor contract law have not reached a consistent conclusion. Studies find that China's labor contract law promotes the transformation of China's industries (Huang, 2012), and facilitates enterprise innovation (Ni & Zhu, 2016). Moreover, it has improved the quality of enterprises' export products (Li & Yang, 2021). Besides, the law has also brought negative problems such as decreasing business elasticity (Liao & Chen, 2014), increasing stickiness of labor costs (Liu & Liu, 2014), and reducing investment efficiency (Lu et al., 2015; Pan & Chen, 2017).

In recent years, there has been growing interest in the influence of NLCL on workers' welfare. Most studies show that the implementation of the policy has significantly improved workers' welfare. A study in the Pearl River Delta region by Li and Freeman (2013), demonstrated that the NLCL increased the proportion of signing labor contracts, expanded social insurance coverage and reduced violations of workers' legal rights. Similarly, Gallagher (2015) showed that since the implementation of the NLCL increased the prevalence of labor contracts, employment security as well as social insurance has also been enhanced. Du et al. (2018) focused on rural migrant workers, and analyzed the impact of the NLCL on their legal rights. The results showed that the law significantly improved the welfare status of the migrant workers, and that the effects of on labor-related social benefits are stronger for migrant workers with lower bargaining power or lower education levels. By contrast, a study based on CHNS data by Chen and Liu (2014) concluded that the income gap between employment with disabilities and those in general employment widened significantly after the implementation of the NLCL. It means that strict labor protection cannot completely make up for the treatment differences brought about by the market, but only transform the treatment differences from the contract guarantee into the income level.

The existing literature have shown the beneficial effects of the implementation of NLCl on workers' welfare. However, there has been no discussion on the role played by the NLCL in terms of human capital investment, but only in the heterogeneity analysis section comparing the differential effects of the NLCL according to workers' educational attainment groupings, as in Gallagher (2015) and Du et al. (2018). Since household investment in human capital affects education opportunities and social mobility, making it a central focus for labor and education economists. Previous studies have extensively explored the various factors that influence household education expenditure at the micro level, with the most commonly discussed factor being household income (Filmer & Pritchett, 1999; Glewwe & Jacoby, 2004; Chi et al., 2012). Other factors that have been considered include parental education level (Su & Liu, 2020), family social status (Zhou & Zhang, 2015), socio-cultural capital (Fan & Lin, 2021), and etc. However, the impact of macro level policy factors on household education expenditure has received less attention from researchers. By matching local financial data with micro data from a sample survey, Yuan et al. (2013) delved into the intriguing relationship between local education expenditure and the education expenses incurred by primary and secondary school students' households. Gao et al.'s (2014) research using CHIP 2007 data revealed that policy subsidies, like Dibao, can improve the education spending of low-income households and therefore enhance human capital. Liu and Liu (2020) explored the effects of individual income tax reform on household education expenditure, utilizing a difference-in-differences approach. Their findings demonstrated that the reform raised education spending, and mitigated the weight of education expenses on households, narrowing the education expenditure gap.

Overall, previous studies have primarily focused on the effects of the NLCL on enterprises and industries, with limited research on the impact on workers at the individual level. There is a lack of literature on macro and institutional factors influencing family education expenditure, and no studies have explored the effects of the NLCL on this aspect through the lens of protecting the rights of vulnerable workers. As one of the most stringent labor protection policies in China, the implementation of the NLCL has not only directly affected the labor welfare of migrant workers, but also may lead to an increase in household education expenditure for this group. This paper aims to answer the following questions: Does the implementation of the NLCL lead to an increase in household education expenditure for migrant workers? What is the magnitude of this impact? Are there heterogeneous effects on migrant workers' families with different characteristics, and what are the mechanisms of these effects? In order to answer these questions, this paper examines the impact of the NLCL on the education expenditure of migrant workers' families, using the implementation of the NLCL in 2008 as a quasi-natural experiment to assess the influence of the policy on this group, and explores its heterogeneous effects and impact mechanisms, thus forming an important addition to the relevant literature.

III. Model Setting, Data Sources and Sample Selection

(i) Baseline model setting

The baseline empirical strategy adopted in this paper is the difference-in-differences (DID) method under a multiple regression model, as applied to the policy shocks created by the enactment of the NLCL. The DID method allows us to isolate the causal effects of the NLCL by comparing the differences in outcomes between the treatment and control groups before and after the policy was implemented. We consider the sample of migrant workers as the treatment group and the sample of non-civil servants with urban household registration as the control group, as shown by Du et al. (2018). Because of the hukou system in China, there has been a dual labor market in cities (Chan & Zhang, 1999). Labors with local non-farm household registration have priority protection for their interests(Afridi et al., 2015;Liu, 2005). Prior to the NLCL, the regulatory environment was not as strict. Enterprises fulfilled their obligations more consistently for local urban household registration labors (Pi and Zhang, 2016; Tan et al., 2022). The NLCL significantly increased the protection for migrant labors, Instead, urban workers' labor interests were already well protected and were not significantly affected by the NLCL (Ding, 2010), thus forming a good contrast with the migrant labors.

In this analysis, the dummy variable du representing treatment group is set to 1 for the sample of migrant workers and 0 for the control group, and the time dummy variable dt is used to distinguish between the pre- and post-NLCL implementation periods., with the year before 2008 assigned a value of 0 and 1 otherwise. This allows us to estimate the effect of the NLCL on human capital investment using the following regression model (equation 1):

$$Y_{it} = \beta_0 + \beta_1 du_{it} + \beta_2 dt_{it} + \beta_3 du_{it} \times dt_{it} + \delta \cdot \because_{it} + \varepsilon_{it} \quad (1)$$

where Y_{it} represents the level of household education expenditure for individual i at time t ; the coefficient β_3 of $du_{it} \times dt_{it}$ is the parameter of interest, representing the impact of the NLCL on education expenditure for the migrant worker group; $\because_{it}$ denotes other control variables that may affect education expenditure, such as age, education level, health level, household income per capita, number of children; ε_{it} is the residual term.

(ii) Data sources

The data used in this paper are derived from the China General Social Survey (CGSS) 2006 and 2010, as well as the China Comprehensive Social Survey (CSS) 2013. The CGSS employs a stratified design and multi-stage probability-proportionate-to-size (PPS) sampling method, providing a high level of representativeness and credibility for the collected data. However, as the CGSS data for 2003, 2005, 2008, and 2013 do not include information on household education expenditure, the focus of this paper, and the CGSS 2015 data on this variable has a high number of missing values and is not representative, this analysis only uses data from CGSS 2006 and 2010.

In order to improve the reliability of the results, this study also incorporates data from the CSS 2013. The CSS is a nationwide continuous sample survey project initiated by the Institute of Sociology of the Chinese Academy of Social Sciences, covering 31 provincial administrative units in China. The questionnaire includes questions on labor and employment, family situation, social life, and social attitudes. Despite being carried out by different units, the CGSS and CSS have a high degree of consistency in terms of survey respondents and questionnaire design, allowing for the use of comparable data.

It should be noted that the robustness check section of this analysis also employs data from the China Household Income Survey (CHIP), a collaborative project between the Chinese Academy of Social Sciences and Beijing Normal University. The CHIP includes the Rural Household Survey, the Urban Household Survey, and the Migration Survey, and has a high degree of consistency with the CGSS and CSS in terms of survey respondents and questionnaire design. It also records detailed information on individual age, education level, marital status, household income, and expenditure.

The regional control variables utilized in this paper are derived from the China Statistical Yearbook. As each round of the CGSS and CSS asks about the previous year, for example, the 2006 survey corresponds to 2005, this paper uses regional control variables from 2005, 2009, and 2012 to match the project survey data from 2006, 2010, and 2013, respectively.

(iii) Sample selection issues

In the setting of equation (1), a direct difference-in-differences estimation may face the problem of selective bias due to two factors. Firstly, the implementation of the NLCL may increase the propensity of farmers to choose to work, potentially leading to the characteristics of migrant workers are different from those of farmers who stay in villages. Secondly, the policy effectively safeguards the labor rights and interests of migrant workers, allowing those with higher individual ability to accumulate capital quickly and successfully complete the task of going out to work, which will cause the group affected by the NLCL to be negatively related to their actual ability. These possible confounding factors make direct difference-in-differences estimation subject to selective bias due to non-random sampling (Du, et al., 2018). To address this issue, this analysis employs a year-by-year propensity score matching (PSM) approach with both farming and migrant worker samples. A range of exogenous factors that may influence rural individuals' choice to work are selected, including gender, age, education level, health status, and marital. Propensity scores are calculated using a logit model and the nearest neighbor matching method is used to identify the different group individuals with the highest propensity scores. The quality of the PSM is tested for balance, with results indicating that after the matching procedure, there is no systematic difference between the samples and sample selection bias is largely eliminated.

To ensure the quality of the PSM, we conduct a balance test. As presented in Table 1, the differences shown by each statistic decrease to varying degrees after matching. For example, the Pseudo-R^2 drops from 0.116 and 0.18 before matching to 0.004 and 0.01, while the LR statistic decreases from a range of 176.3 to 1271.79 to 20.07 to 35.24. Additionally, the mean and median deviations both fall within the range of 5.2%, and the B value also significantly decreases. These results suggest that after implementing the PSM, there is no longer a systematic difference between the treatment group and control group, effectively mitigating the potential bias introduced by sample selection.

Table 1 **Balance test results**

	Pseudo-R^2	LR	Mean deviation (%)	Median deviation (%)	B-value
2006					
Before	0.116	789.43	37.7	34.4	85.2*
After	0.004	22.07	3.0	1.9	14.2

2010					
Before	0.180	1271.79	47.7	42.9	108.8*
After	0.004	20.32	4.0	3.5	15.7
2013					
Before	0.116	176.30	37.8	23.5	93.4*
After	0.010	35.24	5.2	3.5	23.4

Based on the aforementioned processing, we divide the sample into four groups: agricultural workers, migrant workers, urban civil servants, and urban non-civil servants. Due to the fact that agricultural workers do not have regular employers, their employment characteristics are significantly different from other groups, and the educational investment in rural areas is much lower than that in urban areas, we utilize the agricultural worker sample solely to address selection bias, but exclude it from our subsequent analysis. For urban workers, the civil servant group is more stable in terms of work and income, and generally has better benefits than the non-civil servant group, so it is necessary to divide the urban workers into civil servant and non-civil servant groups. We choose the urban non-civil servant sample, which is more similar to the migrant worker characteristics in the labor market, as the control group, and include the urban civil servant sample in the subsequent robustness test. In line with the research objectives of this paper, we use the PSM method to correct for sample selection bias and restrict the sample to workers fully engaged in non-agricultural work. We exclude those with employment identities as corporate partners, individual businesses, unpaid family labor, and self-employed workers, thus retaining all wage earners. Subsequently, we divide the sample based on household registration and employment units, retaining the migrant worker and the urban non-civil servant, and excluding families without children. This results in a sample size of over 4,000 observations. Table 2 provides definitions for the relevant variables, with corresponding descriptive statistics presented in Table 3.

Variables	Definition
lneducost	Log of household education expenditure
peducost	Log of household expenditure on education over number of children
insura1	With medical insurance equals 1, otherwise equals 0
insura2	With pension insurance equals 1, otherwise equals 0
age	Age of respondent in year of interview
party	Communist Party member = 1, otherwise = 0
mid	Completion of lower secondary education and above = 1, otherwise = 0
high	Completion of upper secondary education and above = 1, otherwise = 0
health	Healthy = 1, otherwise = 0
marry	Cohabiting, married = 1, unmarried, divorced, widowed = 0
lnfincome	Log of total household income over total household size

child	Number of children in the family
lngdp	Provincial gross regional product taken as logarithm
struc	Provincial gross tertiary sector over gross secondary sector
lnjumin	Log of consumption levels in provincial areas

Note: All monetary variables are CPI deflated using 2006 as the base period and provincial data are obtained from the China Statistical Yearbook.

Table 3 **Summary statistics**

Variables	2006			2010			2013		
	Obs.	Mean	S. D.	Obs.	Mean	S. D.	Obs.	Mean	S. D.
lneducost	1196	5.542	3.377	1466	5.157	3.871	1357	5.388	3.851
peducost	1196	5.298	3.263	1450	4.964	3.753	1357	5.186	3.731
insura1	1196	0.246	0.431	1462	0.853	0.354	1354	0.897	0.304
insura2	1196	0.235	0.424	1419	0.505	0.500	1351	0.659	0.474
age	1196	40.5	9.257	1466	42.219	9.753	1357	41.655	9.451
party	1196	0.099	0.298	1465	0.126	0.332	1356	0.092	0.289
mid	1196	0.745	0.436	1466	0.776	0.417	1357	0.769	0.421
high	1196	0.334	0.472	1466	0.392	0.488	1357	0.359	0.48
health	1196	0.841	0.366	1464	0.709	0.454	1357	0.808	0.394
marry	1196	0.965	0.184	1466	0.943	0.232	1356	0.963	0.189
lnfincome	1196	8.466	1.047	1466	9.026	1.048	1357	9.158	0.835
child	1196	1.518	0.770	1450	1.503	0.787	1357	1.426	0.653
lngdp	1196	8.856	0.660	1466	9.399	0.814	1357	10.012	0.698
struc	1196	0.924	0.330	1466	1.007	0.581	1357	0.953	0.462
lnjumin	1196	8.636	0.430	1466	9.170	0.432	1357	9.605	0.364

IV. Analysis of the empirical results

(i) Baseline regression results

In this study, we investigate the effect of the NLCL on the education expenditure of migrant workers. Table 4 presents the estimated results using the difference-in-differences method. The explanatory variables in columns 1-4 are the log values of household education expenditure, where column 1 includes only the DID estimation key variable, while controlling for time fixed effects and province fixed effects. Based on the estimated coefficient values from $du \times dt$, we find that the implementation of the NLCL has significantly increased education expenditure for the migrant worker population by 63.4%. Column 2 gradually adds individual control variables into the model, while columns 3 and 4 further include household and regional control variables. By comparing the results of columns 1-4, we can see that regardless of the model specification, the regression coefficient of our focus variable $du \times dt$ is significantly positive, indicating that the implementation of the NLCL has indeed had a significant positive impact on education expenditure for the migrant workers. The main reason for this result may be the strengthened regulatory environment brought about by the implementation of labor protection laws, which has effectively increased the wages and labor benefits of migrant workers, thereby relaxing the budget constraints faced by investing in human capital for the next generation compared to before the implementation of the NLCL.

The results of our analysis indicate that control variables at the individual and household level have a significant impact on household education spending, while those at the regional level do not. Specifically, the age has a negative association with family education spending, while those with a high school education have higher spending on education. Additionally, marital status has a positive association with education spending. The household control variables, such as per capita income and the number of children, also significantly increase education spending. These findings align with previous research in the field.

Table 4 Results of the impact of labor protection on household expenditure on education

Explanatory variables	Explained variable: Household expenditure on education			
	(1)	(2)	(3)	(4)
$du \times dt$	0.634**	0.559**	0.610**	0.572**
	(0.251)	(0.248)	(0.249)	(0.252)
dt	-0.531**	-0.414*	-0.458**	1.534
	(0.216)	(0.213)	(0.215)	(1.845)
du	-1.013***	-0.883***	-1.109***	-1.080***
	(0.201)	(0.212)	(0.218)	(0.220)
Individual control variables				
age		-0.071***	-0.082***	-0.081***
		(0.007)	(0.007)	(0.007)
party		0.186	0.127	0.122
		(0.205)	(0.205)	(0.205)
mid		0.164	0.240	0.239
		(0.153)	(0.153)	(0.153)
high		0.301**	0.306**	0.309**
		(0.145)	(0.147)	(0.147)
health		-0.015	-0.023	-0.018
		(0.143)	(0.143)	(0.143)
marry		0.751**	0.592**	0.598**

		(0.291)	(0.292)	(0.292)
Household control variables				
lnfincome			0.163**	0.164**
			(0.072)	(0.072)
child			0.622***	0.618***
			(0.094)	(0.094)
City-level				
lngdp				0.082
				(1.404)
struc				-0.881
				(0.630)
lnjumin				-2.162
				(1.691)
Constant term	6.184***	8.014***	6.385***	25.153
	(0.151)	(0.507)	(0.789)	(13.670)
Year fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
No. of observations	4019	4014	3999	3999

Note: Standard errors in parentheses are clustered at the provincial level: ***p<0.01, **p<0.05, *p<0.1.

(ii) Robustness tests

To further verify the reliability of the aforementioned research findings, we perform a series of robustness tests to exclude potential confounding factors on the research conclusions.

1. Use education expenditure per child as the explanatory variable

After the revised NLCL enhanced protection of the rights and interests of workers, it is possible that migrant-worker families may have more children, leading to an increase in overall education spending within the household. Therefore, in order to eliminate the interference of the number of children on the total amount of family education expenditure, we use the average education expenditure per child as the dependent variable, and the regression results are shown in Table 5. The results show that the regression coefficients for $du \times dt$ are all significantly positive, and the differences are relatively small compared to the regression coefficients in Table 4, indicating that the conclusions remain robust even after controlling for the number of children.

Table 5 **Robustness test - replacing the explanatory variables**

Explanatory variables	Explained variable: per child education expenditure			
	(1)	(2)	(3)	(4)

$du \times dt$	0.741***	0.664***	0.652***	0.615**
	(0.244)	(0.240)	(0.242)	(0.244)
dt	-0.526**	-0.414**	-0.482**	1.547
	(0.213)	(0.208)	(0.211)	(1.789)
du	-1.283***	-1.118***	-1.156***	-1.128***
	(0.195)	(0.204)	(0.211)	(0.213)
Individual control variables	No	Yes	Yes	Yes
Household control variables	No	No	Yes	Yes
Area control variables	No	No	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	4019	4014	3999	3999

Note: Standard errors in parentheses are clustered at the provincial level: ***p<0.01, **p<0.05, *p<0.1. Control variables are all individual control variables, household control variables and area control variables in Table 4.

2. Include government officials in the control group

The previous control group only consisted of urban non-government officials, but Du et al. (2018) also attempt to include government officials in the control group. Thus, we sought to include urban household samples of government officials in Table 6 to assess the reliability of our results. For example, the results in Column 4 show that the implementation of the NLCL significantly enhanced the household education expenditures of the migrant workers, with an effect of approximately 39.3%. This indicates that even when comparing the government officials with migrant workers, the positive impact of the NLCL on the household education expenditures of migrant workers remains apparent.

Table 6 **Robustness test - replacement of the control group**

Explanatory variables	Explained variable: Household expenditure on education			
	(1)	(2)	(3)	(4)
$du \times dt$	0.448**	0.342*	0.429**	0.393*
	(0.195)	(0.194)	(0.199)	(0.201)
dt	-0.422***	-0.291**	-0.395***	0.873
	(0.138)	(0.136)	(0.141)	(1.481)
du	-1.046***	-0.713***	-0.910***	-0.884***
	(0.158)	(0.171)	(0.179)	(0.181)
Individual control variables	No	Yes	Yes	Yes
Household control variables	No	No	Yes	Yes

Area control variables	No	No	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	6717	6709	6294	6294

Note: Standard errors in parentheses are clustered at the provincial level: ***p<0.01, **p<0.05, *p<0.1. Control variables are all individual control variables, household control variables and area control variables in Table 4.

3. Add sample from another database

As the original sample only had data for one period (2006) prior to the implementation of the NLCL in 2008, in order to enhance the credibility of our estimation results, we augmented the original data with data from the China Household Income Survey (CHIP). Due to the lack of data on urban household education expenditures and other key control variables in the CHIP 2002, we only incorporated the CHIP 2007 data into the original sample. In order to ensure comparability across different databases, we have carried out the following steps: firstly, nine provinces covered by the 2007 urban household survey and the 2007 migrant population survey are taken as the basis, and the data from other provinces in other years are removed; secondly, considering that the sample size of CHIP 2007 is too large, we set the weights of all CGSS 2006 samples to 1, and the weights of other years are set to the ratio of the 2006 sample size to the sample size of this year, in order to avoid the biased estimation results caused by the imbalanced sample size.

Table 7 presents the results of double-difference estimates using replacement data, where the explanatory variables in columns 1 and 2 represent household education expenditure, and columns 3 and 4 represent per capita education expenditure. The findings of Table 7 suggest that even after replacing the data, the implementation of the NLCL continues to significantly increase both household and per child education expenditure among migrant workers. Moreover, the regression coefficient $du \times dt$ in Table 7 is higher than those previously reported, which may be attributed to the fact that the sample of the survey after data replacement is mainly drawn from provinces with a higher level of development, such as Shanghai, Zhejiang, and Jiangsu, where the NLCL provides stronger protection for workers, leading to a more noticeable effect on increasing household education expenditure.

Table 7 Robustness testing - replacement data

Explanatory variables	Household expenditure on education		Per child education expenditure	
	(1)	(2)	(3)	(4)
$du \times dt$	3.631***	3.582***	3.506***	3.471***
	(0.249)	(0.263)	(0.244)	(0.257)
dt	-2.247***	0.384	-2.110***	0.162
	(0.275)	(1.824)	(0.268)	(1.767)
du	-4.049***	-4.121***	-4.064***	-4.045***
	(0.107)	(0.120)	3.506***	3.471***
Control variables	No	Yes	No	Yes

Time fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	5963	5789	5933	5789

Note: Standard errors in parentheses are clustered at the provincial level: ***p<0.01, **p<0.05, *p<0.1.
Control variables are all individual control variables, household control variables and area control variables in Table 4.

4. Placebo test - randomly generated pseudo treatment group

To further verify whether the estimated results in this paper are driven by unobservable factors such as family, province, and year, this paper conducts a placebo test through the random generation of a placebo group. After controlling for individual and family characteristics, as well as fixed effects for region and time, we conduct 500 difference-in-differences estimations and analyze the distribution of the estimated coefficients. As can be seen from Figure 1, the DID estimations are mostly concentrated around zero, with only a few (eight) deviating from the estimated coefficient obtained using real data (0.572). Furthermore, the majority of p-values are greater than 0.1, rejecting the null hypothesis that the estimated results of the placebo test do not differ from the true estimates. This result indicates that the implementation of the NLCL has a relatively robust effect on the education expenditure of migrant-worker families, and the benchmark regression results are not caused by accidental factors at the family, province, or year levels.

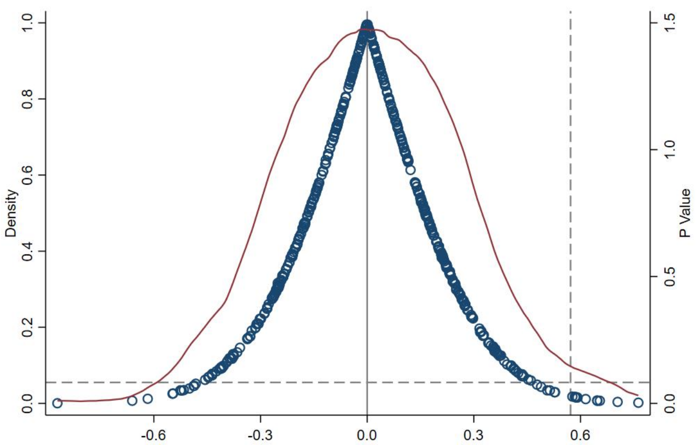

Figure 1 Placebo test - randomly generated pseudo-treatment group

Note: The x-axis indicates the estimated coefficient values from the 500 randomly assigned treatment groups, the curves are the estimated coefficient distributions for the random sample, and the dots are the associated p-values. The vertical line is the true estimate in column 4 of Table 4.

5. Placebo test - fictitious policy time

In addition to the implementation of the NLCL, other contemporaneous policies or random factors may also affect the family education expenditure of workers. To exclude the influence of such factors, we conduct a counterfactual test by changing the policy implementation time. Assuming that the NLCL was implemented in 2010 instead of 2008, if the estimated coefficient of the DID method is still significantly positive, it demonstrates that the increase in family education expenditure of migrant workers may come from other factors, rather than the NLCL. Table 8 shows that the estimated coefficient $du \times dt$ is not significant under the assumption that the NLCL was implemented in 2010, indicating that the increase in family education expenditure of migrant workers is not caused by other factors, but by the implementation of the new law.

Table 8 Placebo test - fictitious policy time regression results

Explanatory variables	Explained variable: Household expenditure on education			
	(1)	(2)	(3)	(4)
$du \times dt$	0.242	0.258	0.354	0.344
	(0.280)	(0.273)	(0.272)	(0.273)
dt	-0.295	-0.236	-0.322	1.603
	(0.241)	(0.236)	(0.239)	(1.847)
du	-0.645***	-0.569***	-0.786***	-0.778***
	(0.148)	(0.159)	(0.165)	(0.166)
Individual control variables	No	Yes	Yes	Yes
Household control variables	No	No	Yes	Yes
Area control variables	No	No	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	4019	4014	3999	3999

Note: Standard errors in parentheses are clustered at the provincial level: ***p<0.01, **p<0.05, *p<0.1. Control variables are all individual control variables, household control variables and area control variables in Table 4.

V. Analysis of heterogeneity and exploration of influence mechanisms

(i) Heterogeneity analysis

The heterogeneity of workers and their households may affect the impact of the NLCL on family education spending, so we investigate this issue using subgroup regression analysis based on the education level of the worker, number of children, and family income level.

1. By education level

Higher parental education is associated with higher education expectations and greater investment in children's education (Tilak, 2002; Su & Liu, 2020; Liu & Yuan, 2021). Therefore, the impact of the NLCL on education spending may be larger for families with higher education levels. To test this hypothesis, we divide the sample into two groups based on whether they have completed junior high school education. The first and second columns of Table 9 report the regression results of this grouping. The result demonstrates that the NLCL has a significant effect on family education spending for the group that has completed junior high school education, but not for the group that has not completed junior high school education.

2. By number of children

According to Becker's (1960) child quantity-quality substitution theory, more children will disperse parents' resource allocation, and there is a negative relationship between the number of children and family education spending. Therefore, single-child families are able to invest more human capital in their child's growth and development compared to multi-child families, thus the NLCL will also have different effects on family education spending depending on the number of children. As can be seen from the comparison of the results in columns 3-4 of Table 9, the implementation of the law significantly increases education spending for families with one child, but has little effect on families with two or more children, which aligns with Becker's theory.

Table 9 **Results of heterogeneity analysis**

Explanatory variables	Education level		Number of children		Household expenditure on education		
	Education below secondary school	Secondary education	One	Two or more	Low-income households	Middle-income households	Higher-income families
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$du \times dt$	-0.295	0.779***	1.079***	-0.214	0.047	0.952**	0.681
	(0.739)	(0.285)	(0.327)	(0.517)	(0.590)	(0.413)	(0.462)
dt	-3.390	3.330	2.447	-1.722	-1.973	1.617	4.887
	(3.850)	(2.124)	(2.370)	(2.936)	(3.280)	(2.934)	(3.437)
du	-0.187	-1.436***	-1.685***	-0.133	-0.500	-1.379***	-1.533***
	(0.617)	(0.244)	(0.284)	(0.438)	0.047	0.952**	0.681
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	943	3056	2516	1483	1148	1616	1235

Note: Standard errors in parentheses are clustered at the provincial level: ***p<0.01, **p<0.05, *p<0.1. Control variables are all individual control variables, household control variables and area control variables in Table 4.

3. By household income bracket

Income is an important factor that affects family education expenditure (Filmer and Pritchett, 1999; Glewwe and Jacoby, 2004; Chi et al., 2012). As income level rises, parents are better able to provide better education opportunities for their children and invest more in their education. To further explore whether the implementation of the NLCL has different effects on education expenditure across different income groups, we divide households into three levels and perform a subgroup regression. Specifically, we divide each province's annual household income into three levels: low income, middle income, and high income, with each sample accounting for 30%, 40%, and 30% of the total effective sample, respectively.

The regression results for these three income groups are shown in Table 9. The results indicate that the NLCL has a greater impact on the education expenditure of the middle-income group, with an increase of 95.2% compared to the control group. Low-income households, however, face greater survival pressures, which makes education-related expenditure a lower priority. On the other hand, this group of workers has lower human capital levels and is often employed in the informal sector, where they are less protected by the new labor contract laws. Therefore, the impact of the new Labor Contract Law on their household education expenditure is weaker. High-income households already have sufficient investment in their children's human capital, so the influence of the new law is not significant.

(ii) Mechanisms of the impact of the NLCL on household education expenditure

The NLCL states that enterprises must provide social insurance for their workers, and sets strict requirements for this. Firstly, social insurance is included among the nine mandatory clauses in the employment contract, and benefits must be negotiated equally with the trade union or workers' representatives[4]. Secondly, if an employer fails to pay full and timely social insurance contributions, the worker can request to terminate the contract, and the employer must pay compensation[5]. Finally, the government has taken active measures to ensure workers' access to insurance benefits, by establishing and improving the inter-regional transfer of workers' social insurance relations, and making employers' payment of social insurance premiums a key part of supervision and inspection[6]. Thus, the law provides incentives and supervision for enterprises to purchase social insurance in full and on time.

We will explore how the NLCL affects education expenditure in two significant ways: pension insurance and medical insurance. Firstly, pension insurance provides income security in old age, mitigating risks from uncertain future income or events, reducing individuals' need to save (Attanasio and Brugiavini, 2003), and thus increasing their lifetime income levels. Based on the theory of permanent income consumption, an increase in lifetime income levels changes the population's consumption expectations, increasing their consumption levels (Fang & Zhang, 2013), and further increasing the possibility for workers to invest in family education. Secondly, health insurance has a positive impact on education investment by improving health and reducing medical costs for households. This allows residents to access better health care and improve their health, particularly for those of lower socioeconomic status (Pan & Qin, 2014). Good health allows individuals to work more and earn more, which in turn increases their ability to invest in education. It also increases the life expectancy of workers, encouraging them to invest in their own human capital and the education of future generations (Wang & Wang, 2021). Over time, health insurance reduces health care costs for individuals and households, freeing up more resources for education spending (Zhang & Zhao, 2020).

Table 10 demonstrates mechanisms for the impact of the NLCL on household education expenditure. Columns 1 and 3 in Table 10 show the Probit model results, and columns 2 and 4 show the corresponding marginal effects. It shows that the introduction of the NLCL resulted in an increase of 14.7% and 31.5% in the probability of obtaining pension insurance and medical insurance, which ultimately affects household education expenditure.

[4] Article 4, Article 17 of the Labour Contract Law
[5] Article 36, Article 48 of the Labour Contract Law
[6] Articles 38 and 74 of the Labour Contract Law

Table 10 **Mechanisms analysis**

Explanatory variables	Pension insurance		Medical insurance	
	(1)	(2)	(3)	(4)
$du \times dt$	0.372***	0.147***	0.954***	0.315***
	(0.113)	(0.045)	(0.110)	(0.037)
Control variables	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
No. of observations	3948	3948	3987	3987

Note: Standard errors in parentheses are clustered at the provincial level: ***p<0.01, **p<0.05, *p<0.1. Control variables are all individual control variables, household control variables and area control variables in Table 4.

VI. Conclusion

As an important legal system that protects workers' legitimate labor rights and interests, the NLCL has significantly impacted the economic behavior of enterprises and individual workers' welfare since its implementation. In contrast to previous literature that focused on workers' own welfare, this paper assesses the impact of the NLCL on the human capital investment of migrant workers' households, which is crucial for maximizing the impact of labor protection policies on addressing educational inequity and promoting educational mobility.

Based on CGSS and CSS data, this paper employs a difference-in-differences method to assess the impact of the NLCL on migrant workers' household education expenditure. By utilizing the propensity score matching method, the issue of sample selection bias caused by individual farmers' choice to work is eliminated. Our results show that the implementation of the NLCL significantly increases migrant worker household education expenditure compared to urban households. Additionally, the paper explores the differences in impact by education level, number of children, and household income bracket. The results indicate that the NLCL has a greater impact on household education expenditure among migrant worker with higher education levels and households with one child. Furthermore, the impact is mainly felt by middle-income households, while among low-income and higher-income households, the impact is not significant. The analysis of the mechanism reveals that the NLCL can increase migrant workers' access to pension and medical insurance, reducing the risk of future household expenditure on pension and medical care, thus increase household education expenditure.

The findings of this paper enrich the literature on the evaluation of the policy effects of the NLCL and investment in human capital. We provide a clear answer to the question of whether the NLCL has increased investment in education for disadvantaged employment groups, making this paper a valuable addition to existing research. Our research shows that the NLCL not only protects the legal labor rights and improves labor welfare of the present generation, but also affects the investment in education of the next generation, particularly the children of disadvantaged groups. Furthermore, the NLCL has significantly increased investment in human capital of disadvantaged groups, narrowing the education gap by a certain extent. Therefore, policies related to labor protection should be further improved to fully utilize their role in promoting human capital investment in disadvantaged families, which can more effectively improve education level and promote educational equity and common prosperity.

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