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NOVEMBER 2022

ISSN: 2365-9793

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ABSTRACT

Labor Market Effects of Bounds on Domestic Outsourcing*

We investigate the labor market effects of putting bounds to domestic outsourcing in Peru. A series of difference-in-differences specifications for individuals with high versus low predicted propensities to be outsourced show evidence of non-negative labor market effects. Limiting domestic outsourcing increases labor force participation by 1.5 percentage points and employment by 2.3 percentage points while it reduces unemployment by 0.8 percentage points, but has no statistically significant impact on labor formality nor real wages. Our results suggest that a policy of restricting outsourcing does neither destruct jobs nor does it improve workers' labor market conditions in the short-run.

JEL Classification: J21, J48, E24

Keywords: domestic outsourcing, employment

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* All errors and omissions are our own. The opinions expressed in this publication are those of the authors and do not necessarily reflect the views of the Inter-American Development Bank, its Board of Executive Directors, or the countries they represent.

1 Introduction

Recent studies have documented a steady increase in domestic outsourcing worldwide since around the 1990s (Bloom et al., 2019; Handwerker, 2020; Felix and Wong, 2021). While this trend may have the benefit of reducing labor costs for large employers, study after study finds that it worsens labor market conditions for workers who serve as outsourced manpower. Goldschmidt and Schmieder (2017), Drenik et al. (2021), Bilal and Lhuillier (2021), Dube and Kaplan (2010), and Spitze (2022) find that these workers enjoy lower wages or benefits, such as employer-financed health insurance, than non-outsourced workers.[1] Several governments around the world have responded to this situation by enacting measures to improve outsourced workers' living standards. For example, Mexico and Ecuador have implemented strict bans to outsourcing since 2008, and 2021, respectively. Similarly, in 2022, Spain also enacted a law to severely restrict another non-conventional form of labor contracting: temporary contracts. However, little is known about the labor market effects of limiting outsourcing.

In this article, we study the impact of a very recent policy of limiting outsourcing on outsourcing itself, formality, real wages, labor market participation, employment, and unemployment. In February 2022, the Peruvian government restricted outsourcing for any activity related to the core of the business, under the claim that companies were indicrimately using external personnel to operate. Namely, the restriction forbids the employment of outside labor to perform the most income-producing activity, or that which customers identify the firm with. Nontheless, outsourcing personnel for highly-specialized or specific services, other than the core of the business, remains legal. By providing the first piece of evidence on the labor market effects of limiting domestic outsourcing, we hope to derive lessons of general interest for countries where similar limitations have been recently applied or are being considered.

Our identification strategy grows out from Card and Krueger (2015) and Cengiz et al. (2022). Given that these restrictions can impact the labor market outcomes not only of those workers who are currently outsourced, but also of those who are "at risk" of being hired like so, our identification strategy constructs demographically-based treatment and control groups. Then, we compare a group of individuals with a high outsourcing predicted probability with a group comprised of individuals who are unlikely to serve as outsourced personnel.

[1] This is likely to foster income inequality (Dorn et al., 2018; Deibler, 2021).

After estimating an event study and a canonical difference-in-differences specification using these groups, we find neither a job destruction effect nor an improvement of workers' labor conditions of domestic outsourcing in the short-run. The policy of limiting outsourcing did effectively reduce outsourcing by 25% and increased labor force participation and employment by 1.5 (1.8%) and 2.3 (3%) percentage points, respectively, and reduced unemployment by 0.8 (16%) percentage points. However, it had no statistically significant impact on formality rates and real wages.

2 Data

Labor market and demographic data come from the Quarterly Samples of the Peruvian National Household Surveys (*Encuesta Nacional de Hogares*, ENAHO) between 2021 and 2022. These samples are collected periodically by the National Institute of Statistics and Computing (*Instituto Nacional de Estadísticas e Informática*, INEI) and are representative of the working and non-working populations in each quarter. Each round is comprised of slightly over 20,000 observations each.[2] As of today, we have information for all quarters in 2021 and the first two quarters of 2022. To avoid introducing the COVID-19 pandemic as a confounder, we did not include quarters before 2020. We impose no further ex-ante restrictions on the sample for this study.

For our empirical analysis we need to construct a demographic-based measure of individuals' risk of being outsourced. The Peruvian National Household Surveys are well equipped for this purpose, as respondents declare whenever they work as outsourced personnel for firms that provide third-party contracting services. Moreover, these surveys include a rich set of demographic variables such as sex, age, race, and region.

3 Identification Strategy and Results

Our identification strategy consists of two steps. First, we use a data-driven method to identify treatment and control groups. Second, we estimate an event study and canonical difference-in-differences specifications to recover the causal effects of interest by comparing both groups before and after the bound on domestic outsourcing.

[2]These data are a repeated cross section not a panel data set. Accordingly, we do not observe the same individual at different points in time.

In the first step we estimate the following Probit specification over the sample of individuals who were working in 2021:

$$\begin{aligned} T_i =& \beta_0 + \beta_1 \text{Sex}_i + \beta_2 \text{Married}_i + \beta_3 \text{Region}_i \\ & + \beta_4 \text{Age}_i + \beta_5 \text{Race}_i + \beta_6 \text{Education}_i + \epsilon_i, \end{aligned} \tag{1}$$

The dependent variable T_i is a dummy that indicates whenever an individual reported working as outsourced personnel. We follow Card and Krueger (2015) and introduce a minimalistic set of covariates to the right hand side of this equation. Namely, we characterize individual propensity to being outsourced as a function of their sex, age, marital status, geographical region, race, and education. In Appendix A, we provide further detail on the definition of each variable.

To evaluate the performance of this parsimonious specification we compute the area under the ROC curve and obtain a value of 0.82. This implies that Equation (1) has a more than acceptable accuracy for classifying individuals into outsourced and non-outsourced workers (Hosmer et al., 2013). This resonates with the findings in Cengiz et al. (2022). Namely, it seems that using minimalistic specifications, such as the one in Card and Krueger (2015), yields notably good performances while guarding against the risk of overfitting. Furthermore, in Table 1, we show the demographics of workers in the control group and the treatment group. We also present descriptive statistics for the outsourced personnel in 2021. It is clear that the treatment group more closely resembles outsourced workers than the control group. This reinforces the credibility of our selection of treatment and control groups.

[Table 1 Goes Here]

In the second step, we calculate the predicted probabilities of being outsourced, $\hat{T}_i$, for the entire sample, using Equation (1). With this prediction we construct R_i, our treatment dummy, which takes the value of 1 for individuals with a $\hat{T}_i$ in the top 10%, and of 0, for those in the bottom 50%. As in Card and Krueger (2015), we exclude from the second step estimation individuals with $\hat{T}_i$ between these figures. Then we estimate the following event study specification:

$$y_{i,t} = \alpha_0 + \alpha_1 R_i + \sum_t \delta_t (R_i \times \theta_t) + \theta_t + \mu_{i,t}, \tag{2}$$

where $y_{i,t}$ are a series of labor market outcomes and θ_t are quarter fixed effects. The main coefficients are the δ_t that multiply the interaction term between the treatment and quarter dummies. These represent the difference in labor market outcomes between individuals with a high probability of working as outsourced personnel with those with a low probability, quarter by quarter.

Figure 1, shows the δ_t coefficients obtained after estimating Equation (2) for a series of labor market outcomes.

[Figure 1 Goes Here]

In panel a, we see that outsourcing dropped sharply after the enactment of the bound. Next, in panels b and c, we show that bounding outsourcing has no impact on formality and hints that it might have a small, but short-lasting, positive effect on real wages. When looking beyond the employed population, we see, in panels d, e , and f; that after the policy change, individuals with demographic profiles associated with a higher probability of working as outsourced personnel experience higher labor force participation and employment. The outsourcing bound also caused a drop in the unemployment-to-workforce ratios of those who are less likely to have been targeted by the policy.

To get a better idea of the magnitude of the effects, and to test the robustness of out results we re-estimate Equation (2) as a canonical diff-in-diff. Namely, we replace the quarter fixed effects in the interaction term for a single dummy indicating that the individual was observed after the outsourcing bound, in 2022. This yields a single diff-in-diff coefficient for each outcome. We report the results in Table 2.

[Table 2 Goes Here]

The bound on outsourcing decreased outsourcing by 0.8 percentage points (25%) and had no discernible effects on labor market formality, nor wages.[3] In addition, it increased labor force participation and employment by 1.5 and 2.3 percentage points (or 1.8 and 3%). It also reduced unemployment by 0.8 points (16%).[4]

[3]These results are identical when excluding the self-employed from the sample. The results from this exercise are available upon request.

[4]We do not include any individual-level demographic controls as the treatment assignment is a function of them. This is usual in the literature, see Cengiz et al. (2022). When we include the variables in equation 1 as controls, most results remain qualitatively identical. Nonetheless, the growth in employment and the drop in unemployment become much closer in magnitude so that the effect on labor force participation disappears. The results are available upon request.

4 Conclusion

We have examined the labor market effects of limiting domestic outsourcing. Using demographically-based treatment and control groups and two different specifications, we show that putting bounds on domestic outsourcing does *de facto* reduce outsourcing and increases labor force participation and employment. We also find that limiting outsourcing reduces unemployment and has no impact on labor market formality nor wages. Overall, our results indicate that this policy does not lead to employment destruction, a fear raised by policy-makers worldwide. However, they also show its limited potential for improving workers' labor market conditions as we do not detect material improvements in wages nor labor formality. Further research should establish whether these findings for the short-run persist in the medium and long-run.

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Table 1: Summary Statistics by Group.

Variable/Group	Full Sample (1)	Outsourced in 2021 (2)	Treatment Group (3)	Control Group (4)
Females (%)	52.20	30.50	28.16	59.92
Mean Age	42.19	37.75	36.77	47.02
Race(%)				
Native	31.58	18.62	11.50	39.57
Black	7.11	10.46	13.82	6.40
White	4.18	4.78	5.34	4.06
Mestizo (Mixed-Race)	53.08	59.57	60.92	46.66
Other	4.05	6.56	8.43	3.31
More than High School (%)	26.37	39.89	42.70	11.45
Married (%)	51.87	52.30	46.96	50.38
Lives in Lima (%)	12.14	30.32	52.15	5.72
Obs.	138,240	564	13,773	69,280

Note: the table shows the demographic profiles of three groups. In column 1, we show the composition of the entire sample. In column 2, we describe workers who were outsourced in 2021. In columns 3 and 4, we describe the demographics of individuals in the treatment and control groups. We only include observations with valid information for all covariates.

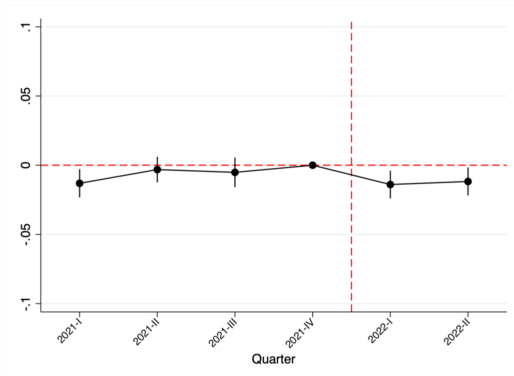
Table 2: The Labor Market Effects of Bounding Domestic Outsourcing. Canonical Difference-in-Differences Specification.

Outcome	$R_i \times Post_i$ (1)	Std. Error (2)	Baseline Mean (3)	Obs. (4)
Outsourced	-0.008**	(0.003)	0.032	57,973
Formality	-0.002	(0.011)	0.342	57,973
Real Wages	0.013	(0.028)	7.091	18,741
Labor Force Participation	0.015*	(0.008)	0.841	88,534
Employment	0.023***	(0.008)	0.790	88,534
Unemployment	-0.008*	(0.004)	0.051	88,534

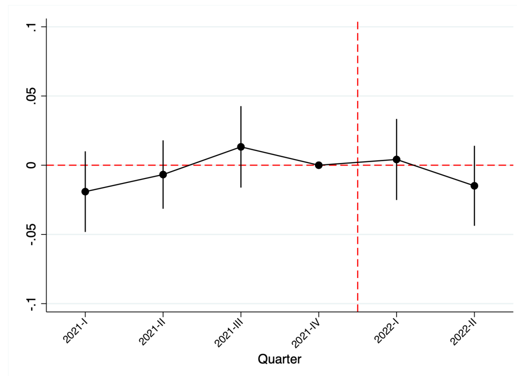
Note: the first column shows the diff-in-diff coefficients. $Post_i$is a dummy that indicates observations collected in 2022. Columns 2 and 3 report robust standard errors and the mean of the treatment group in 2021. Column 4, shows the number of observations used in each regression. *** p <0.01, ** p <0.05, $^{*}p$ <0.1.

Figure 1: Event Study of Domestic Outsourcing Bounds Effects Labor Market Outcomes

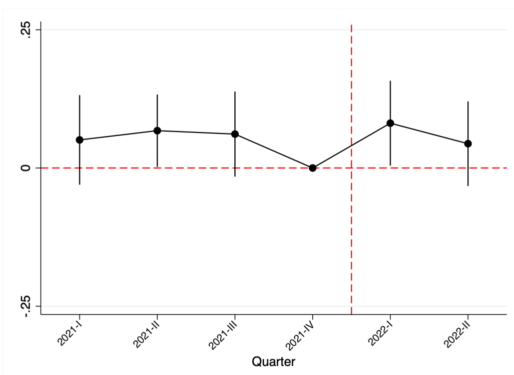
(a) Outsourced.



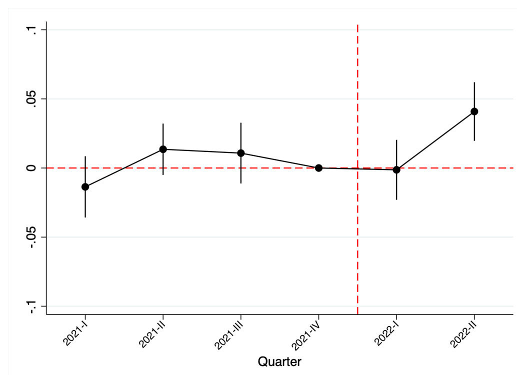
(b) Formality.



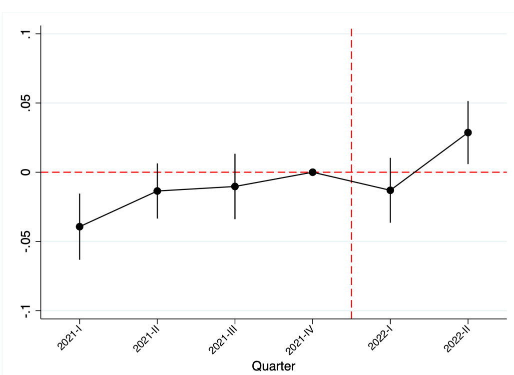
(c) Real Wages.



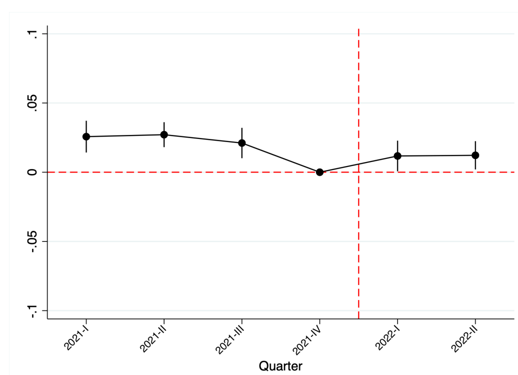
(d) Labor Force Participation.



(e) Employment.



(f) Unemployment.



Note: The figure shows the δ coefficients from equation 2 and their 90% confidence intervals. We set the coefficient for the pre-treatment quarter equal to 0. The dashed vertical line indicates the enactment of the bound on domestic outsourcing.

Appendix

A Definition of the Variables

- Outsourced worker: any worker that is employed by a "special service firm" (i.e., a firm that supplies outsourced labor to other firms).
- Labor force participant: an individual who is employed or unemployed. This variable is provided by Peru's Institute of Statistics and Computing.
- Employed: a dummy that equals 1 for individuals who are employed and 0 for the rest of the population aged 14 and up. This variable is provided by Peru's Institute of Statistics and Computing.
- Unemployed: a dummy that equals 1 for individuals who are unemployed, but actively seeking for a job, and 0 for the rest of the population aged 14 and up. This variable is provided by Peru's Institute of Statistics and Computing.
- Out of the labor force: individuals who are explicitly out of the labor force or are unemployed but not actively looking for a job. This variable is provided by Peru's Institute of Statistics and Computing.
- Formal employment: wage worker without employer-financed social security, or employers who do not report to the tax authorities. This variable is provided by Peru's Institute of Statistics and Computing.
- Real Wages: Constructed from a series of variables that indicate the frequency and amount of each payment received by the worker as a wage. We only consider each worker's main occupation. Monthly wages were deflated using the average Consumer Price Index for each year extracted from the following link: `https://m.inei.gob.pe/estadisticas/indice-tematico/price-indexes/`
- Sex: dummy variable that indicates when a respondent is female.
- Married: dummy variable that indicates when a respondent is married or lives together with their partner.
- Region: a vector of dummy variables that indicate if survey respondents live in the northern, central, or southern coast; the northern, central, or southern highlands, the amazon region or Metropolitan Lima.

- Race: categorical variable that indicates self reported race. The categories are: native, black, white, mestizo (mixed-race), and other.
- Age groups: we group individuals in 5 year age groups from those aged 14 to 64. We group all individuals older than 64 in another group.