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Research paper

The impact of COVID-19 infection on labor outcomes of Mexican formal workers☆

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ABSTRACT

The outbreak of the COVID-19 pandemic had an immediate and severe impact on the economy. However, we do not know whether the disease may have a longer-term effect on people's employment opportunities. In this study, we focus on the effects of COVID-19 infection on labor market outcomes 12 months after diagnosis. We use a unique dataset that includes all formal private sector workers in the Mexican social security system and that links health outcomes with administrative records. We implement two alternative identification strategies to estimate the impact: matching estimators and individual fixed effects models. Our study finds that COVID-19 infection does not harm employment probabilities or wages. On the contrary, we find that workers who had tested positive for COVID had a higher likelihood of keeping their formal sector jobs and higher wages than those who did not. Moreover, our results describe mostly low-income workers.

1. Introduction

The COVID-19 pandemic has had a significant impact on the world economy. Most evidence of this impact documents its macroeconomic effects on consumption, employment, and income (Brodeur et al., 2021). With respect to employment, we know that lockdowns (Bauer & Weber, 2021) and fear of infection (Aum et al., 2021) have led to business closures and high unemployment rates. However, we know very little about the effects of COVID-19 infection on employment and wages at the individual level. This paper aims to fill this gap by analyzing the impact of COVID-19 infection on the labor market outcomes of formal sector workers in Mexico.

Previous research on the economic impact of the COVID-19 pandemic has focused on aggregated indicators, including several that have investigated the effect of the pandemic on economic and labor market outcomes for different countries.[1] We now know that the sociodemographic groups most affected have been those with low wages, low educational levels, and women (Adams-Prassl et al., 2020; Alon et al., 2020; del Rio-Chanona et al., 2020; ILO & OECD, 2020; Moehring et al., 2021). Other studies have used novel data to measure the real-time impact of the pandemic on the economy. A number of these have used real-time data to show how mobility restrictions reduced

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[1] For the United States, see Coibion et al. (2020); Kurmann et al. (2020). For Europe, see Fana et al. (2020); and Pouliakas & Branka (2020). Regarding Latin America, see Ferreira dos Santos et al. (2020) for Brazil; and Modrego et al. (2020) for Chile. For economic models, see Guerrieri et al. (2020) and Pichler et al. (2020).

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consumption by 23 to 60 percent in different regions (Andersen et al., 2020; Baker et al., 2020; Barcellos et al., 2014; Bounie et al., 2020; Campos-Vazquez & Esquivel, 2021; Carvalho et al., 2020; Carvalho et al., 2020; Chetty et al., 2020; Hacıoğlu-Hoke et al., 2020). Other studies have used real-time data to show a significant decline in the number of job ads posted during the pandemic (Campos-Vazquez et al., 2021; Chetty et al., 2020; Forsythe et al., 2020; Hensvik et al., 2021; Marinescu et al., 2020). COVID-19 has not only affected worker and household income, but also tax revenue. Current evidence indicates that local tax revenue in the United States has declined by 5 to 9 percent (Chernick et al., 2021; Clemens & Veuger, 2021). The adverse economic effects of the pandemic may continue until the risk of infection is relatively low (Chetty et al., 2020; Goolsbee & Syverson, 2021).

Despite this rich body of work, we still have scant evidence of how COVID-19 infection may affect labor market outcomes at the individual level. There are various possible associations at this level. One of them arises from the possibility of discrimination in the labor market against people who have been infected. At the beginning of the pandemic there was little information about the modes of transmission of the disease. This uncertainty led to stigma and discrimination against people who were infected or at high risk of infection, such as health care workers (Sotgiu & Dobler, 2020). In Mexico, for example, the Mexico City Council for the Prevention and Eradication of Discrimination (COPRED) received complaints of unjustified firings of workers infected with COVID-19.[2] Thus, stigma and discrimination may lead to lower employment levels for the infected population.

An alternative mechanism relating COVID-19 infection and labor market outcomes is through long COVID, which affects 80 percent of confirmed COVID-19 patients two weeks after the acute phase of the disease (Garg et al., 2021). So-called COVID-19 long haulers experience persistent or recurring symptoms. For instance, Domingo et al. (2021) found over 100 post-COVID-19 sequelae up to 12 weeks after the onset of COVID-19 symptoms, including chronic fatigue, breathing difficulties, depression, anxiety, sleep disturbances, and general pain or discomfort (for instance, myalgia, arthralgia, headaches, sore throat, diarrhea, or vomiting). Other studies have described cognitive impairment or debilitating cardiopulmonary conditions following recovery from the acute phase of COVID-19.[3] These persistent conditions will increase demand for health care and may affect workers' possibility of keeping or returning to their jobs after the acute phase of the disease, as well as their subsequent productivity. Long COVID may thus have a negative effect on labor market outcomes for those who have been infected.

To our knowledge, there are only two studies that have examined the impact of COVID-19 on the individual level. Moehring et al. (2020) surveyed 2,297 people in Germany and asked whether they had been infected with COVID. At the time of the study, only 2 percent of respondents had been infected, so the authors could not explore whether such individuals suffered any labor market disadvantages as a result of their infection. Balgova et al. (2021) used a panel survey in the Netherlands to determine a subjective risk of infection, and found that it was not related to their job search. Neither of these papers evaluated the impact of the disease on individual earnings or employment.

In this study we focus on the effects of COVID-19 infection on labor market outcomes 12 months after diagnosis. We use a unique social security dataset covering all formal private sector workers in the Mexican social security system (Instituto Mexicano del Seguro Social, IMSS), that links health outcomes with administrative records. All workers registered at IMSS who presented COVID-19 symptoms and sought medical care were given a PCR test. We track every worker tested between March and June 2020 for 12 months before and after the test.[4] We then estimate whether a confirmed diagnosis of COVID-19 affected their employment and wages as compared to those who tested negative. To estimate the impact, we implement two alternative identification strategies—matching and individual fixed effects models—that lead to essentially the same results.

Our results indicate that COVID-19 infection does not harm employment probabilities or wages. On the contrary, we find that COVID-positive workers had a higher likelihood of keeping their formal sector jobs and higher wages than COVID-negative workers. However, most of the estimated effects come from low-income workers. One hypothesis is that this subgroup of the IMSS population increased their valuation of IMSS health care after they were infected and avoided changing jobs from the formal to the informal sector. Alternatively, employers may have found it profitable to hire workers who had already recovered from COVID to reduce labor turnover related to new severe infections.

The rest of this paper is organized as follows. Section 2 presents the data sources, processing, and descriptive statistics for our estimating sample. Section 3 explains the methods used to estimate the effect on employment of testing positive for COVID-19. Section 4 presents the results, and Section 5 discusses their significance.

2. Data

The data come from the Mexican Institute of Social Security (Instituto Mexicano del Seguro Social, IMSS), which covers all formal private sector wage workers. Private employers are required by law to register all their employees at IMSS, with information about their earnings. Benefits for workers provided by IMSS include health care services and sick leave. Workers who lose their jobs continue to receive health care for up to eight weeks. IMSS also carries out epidemiological surveillance of infectious diseases, including respiratory infections, and shares this information with the Secretary of Health on a daily basis. As part of this surveillance, IMSS installed triage units in its facilities to test suspected cases of COVID-19, using polymerase chain reaction (PCR) tests.

Since the start of the pandemic, the definition of a suspected case has changed from imported cases to community transmission. In March 2020, a suspected case was any person with respiratory symptoms who had traveled to China or was in direct contact with a confirmed case. By mid-April, the definition of a suspected case had changed to any person with at least two of the main COVID symptoms (cough, fever, or headache) and at least one of the following minor symptoms: joint or muscle pain, difficulty swallowing, runny nose or eyes, diarrhea, vomiting, chills, sweating, fatigue, or weakness (Secretary of Health, 2020). Those with chest pain or shortness of breath were given an immediate PCR test to confirm the diagnosis. People suspected of COVID-19 infection were asked to complete a questionnaire about their history of comorbidities: cardiovascular disease, hypertension, kidney disease, tuberculosis, cancer, chronic obstructive pulmonary disease, diabetes, asthma, immunosuppression, HIV, obesity, and smoking.

Our database includes all formal sector workers who took the PCR test at IMSS facilities from March to June 2020 and were between 18 and 75 years old at the time of the test. Health outcomes in the data include the test date, test result, history of comorbidities, and date of death, if applicable. This health information was merged with the IMSS

[2] We thank Geraldina González de la Vega for granting us access to redacted versions of discrimination complaints related to COVID-19.

[3] Garg et al. (2021) mention that several practitioners' guidelines "have divided COVID-19 infection in 3 phases –'Acute COVID-19' (signs and symptoms of COVID-19 infection up to 4 weeks), 'ongoing symptomatic COVID-19' (from 4 weeks up to 12 weeks), and 'post-COVID-19 syndrome' (when signs and symptoms continue beyond 12 weeks)" (p. 2492).

[4] For these workers, we observe all their test results through mid-January 2021. We restrict to June 2020 because we need to observe whether the worker was tested later to be sure that we are comparing COVID positives and negatives, and not seeing a worker who tested negative but months later tested positive.

employment database at the individual level. IMSS reports employment data as of the last day of each month. Of those tested through June 2020, we observe all their test results through mid-January 2021. We focus only on those workers who tested positive on their first test and on those who tested negative on their first test and did not subsequently test positive. We obtain each person's labor trajectory 12 months before and after the test, including formal employment status, earnings, age, and gender. Thus, our dataset at the worker level includes data from March 2019 to June 2022.[5]

We restrict the analysis to those who survived for a year after the test. Mortality was 9.6 percent for those testing positive and 3.0 percent for those testing negative. By definition, because of the associated mortality, COVID-19 has decreased overall employment among those tested. However, our goal in this study is to compare the employment outcomes between surviving workers testing positive and negative. Restricted to workers who survive the disease, the sample size is 52,208 testing positive and 43,941 testing negative.[6] The sample is balanced over 25 months: 12 months before the test, the month of the test, and 12 months after the test.

Table 1 shows selected descriptive statistics for the complete sample (panel A) and the matched sample (panel B; described below); the complete statistics can be found in the Supplementary Materials. In general, differences in observable characteristics between those testing positive and negative for COVID are statistically significant. Those testing positive were more likely to be male and older than those testing negative, and were more likely to suffer from hypertension, diabetes, and obesity. They were equally likely to be formally employed a month before the test, though not in the previous months, and have lower earnings.

Table 1
Descriptive Statistics.

Variable	COVID Negative	COVID Positive	Difference	Std. Error	P-value
A. Full Sample					
No. of observations	43,941	52,208			
Age	38.5	39.9	1.429	0.065	0.000
Female	0.565	0.463	−0.103	0.003	0.000
Hypertension	0.120	0.133	0.014	0.002	0.000
Diabetes	0.073	0.092	0.020	0.002	0.000
Asthma	0.051	0.031	−0.020	0.001	0.000
Smoking	0.088	0.073	−0.014	0.002	0.000
Obesity	0.154	0.184	0.030	0.002	0.000
$Work_{t-9}$	0.891	0.904	0.013	0.002	0.000
$Work_{t-8}$	0.898	0.910	0.012	0.002	0.000
$Work_{t-4}$	0.922	0.931	0.009	0.002	0.000
$Work_{t-1}$	0.968	0.969	0.001	0.001	0.428
$Wage_{t-9}$	569.8	496.6	−73.2	2.791	0.000
$Wage_{t-8}$	576.8	501.9	−74.9	2.806	0.000
$Wage_{t-4}$	619.7	540.4	−79.3	2.936	0.000
$Wage_{t-1}$	661.0	572.6	−88.4	2.929	0.000
B. Matched Sample					
No. of observations	17,238	33,808			
Age	39.1	39.2	0.025	0.087	0.769
Female	0.511	0.511	0.000	0.004	1.000
Hypertension	0.095	0.095	0.000	0.003	1.000
Diabetes	0.062	0.062	0.000	0.002	1.000
Asthma	0.018	0.018	0.000	0.001	1.000
Smoking	0.051	0.051	0.000	0.002	1.000
Obesity	0.144	0.144	0.000	0.003	1.000
$Work_{t-9}$	0.916	0.915	−0.001	0.002	0.622
$Work_{t-8}$	0.921	0.921	0.000	0.002	1.000
$Work_{t-4}$	0.939	0.938	−0.001	0.002	0.781
$Work_{t-1}$	0.978	0.977	−0.001	0.001	0.522
$Wage_{t-9}$	445.6	446.9	1.4	3.131	0.659
$Wage_{t-8}$	449.4	451.1	1.7	3.141	0.588
$Wage_{t-4}$	479.5	481.3	1.8	3.277	0.590
$Wage_{t-1}$	514.3	515.2	0.9	3.304	0.781

Notes: Authors' calculations. Wages are in daily earnings in current Mexican pesos. The matching algorithm uses exact matching for the month of the test, gender, and whether the worker was employed in the months *t*-12, *t*-11, *t*-7, *t*-6, *t*-3, and *t*-2 with respect to the month of the test. In addition, it searches within those groups using the Mahalanobis distance for earnings for the same months as the exact matching, for age, and for all comorbidities. Matching is restricted to observations with a Mahalanobis distance less than 0.5.

3. Methods

As already noted, there are statistically significant differences between workers who test positive and negative. In particular, positivity rates are correlated with both employment probability and mean wages before testing. Therefore, we need to find an appropriate control group among workers testing negative to compare with the treatment group of workers testing positive. Given that we do not have a natural experiment, we use two methods to identify the effect on labor market outcomes of testing positive versus testing negative. First, we use a nearest-neighbor matching algorithm with replacement (Abadie & Imbens, 2006, 2011) that has been widely used (see, for example, Campello & Graham, 2013; Cicala, 2015; Deryugina et al., 2020; Fowlie et al., 2012; Garip, 2014). Second, as a robustness check, we use a fixed effects regression.

The matching algorithm uses exact matching for the month of the test, gender, and whether the worker was employed in the months *t*-12, *t*-11, *t*-7, *t*-6, *t*-3, and *t*-2 relative to the month of the test. It also searches for potential controls using the Mahalanobis distance for the following variables: earnings for the same months as the exact matching, age, and all comorbidities. We restrict the matched sample to those controls with a Mahalanobis distance less than 0.5. This process kept 65 percent of the treatment observations. The average treatment effect on the treated (ATT) is bias-adjusted for earnings and age.[7] We estimate standard errors using influence functions, following Jann (2019). This method obtains standard errors that are conservative compared to other adjustments, but it is still efficient in terms of computer performance, an important consideration given the size of our dataset.[8]

One disadvantage of this method is that we lose observations in the treated group, making it more difficult to analyze the impact on all individuals who tested positive. As a result, we also provide results using a fixed effects regression. We create groups by the month of the test, gender, age groups (younger than 30, 30–44, 45–59, and older than 60), number of jobs in the 12 months before the test, and ventiles of income using average earnings in the 12 months before the test.[9] This method allows us to compare all individuals who tested positive to those who tested negative within specified groups. For instance, it compares individuals of similar age, gender, test month, previous earnings, and labor market attachment. The identifying assumption relies on the test result being random within the specified groups. To further strengthen

[5] We restrict to workers who tested positive or negative up to June 2020 for two reasons. First, at the beginning of the pandemic, testing was limited to public health sector facilities, including IMSS. Second, we need to observe whether the worker was tested later to be sure that we are comparing COVID positives and negatives, and not seeing a worker who tested negative but months later tested positive.

[6] Mexico has had one of the world's highest positivity rates of the pandemic. See https://ourworldindata.org/grapher/covid-19-positive-rate-bar.

[7] The Supplementary Materials explain the steps followed in greater detail.

[8] Jann (2019) performs simulations comparing standard errors using the methodology of Abadie and Imbens (2006, 2011) and influence functions. In general, standard errors are slightly larger using influence functions.

[9] Yagan (2019) includes previous earnings in the fixed effects model in his analysis of long-term labor market effects of the Great Recession. Our analysis follows his approach.

the validity of this assumption, we control for comorbid disease, age, monthly earnings, and employment status for each month in the 12 months before the test.

The matching algorithm is highly successful in balancing observable characteristics. Table 1, panel B shows very similar age, gender, comorbidities, and employment trajectories between those testing positive and negative. In addition, Fig. 1 shows the balance in terms of previous employment and earnings using the matched sample across the wage distribution. First, we calculate the proportion of months out of 12 the individual is formally employed before the test, and average earnings in the same period (obtaining the log of the wage plus one for each period and then taking the average). Next, we calculate ventiles using the matched sample and plot the average for positive and negative tests. The figure shows that formal employment and wages are almost identical across the wage distribution between those who tested positive and negative. Individuals at the bottom of the distribution do not seem to have a strong attachment to the formal sector. However, above the 40th percentile, most workers included in the sample worked in the formal sector during the previous 12 months.

The Supplementary Materials include additional statistics to show the balance between the matching and fixed effect regressions for the labor market outcome trajectories. The average treatment effect over the 12 months prior to the test is zero for both employment and wage with both methods.[10] The Supplementary Materials also include a discussion of the different models used to achieve balance. In general, different matching algorithms provide similar results for both employment and wage outcomes.

4. Results

Fig. 2 shows the main results of the study for both employment and earnings, with matching and fixed effects regression estimates and 95 percent confidence intervals for each period. In the month of the test, there is a small positive effect in employment for those who tested positive relative to those who tested negative, although it is not statistically significant. However, as time progresses, the impact on employment is more marked; those who tested positive are more likely to remain employed than those who tested negative. Six months after the test, the effect is around 1.3 percentage points for both estimates. As most workers had a job at the time of testing, this estimate implies that employment has increased by approximately the same percentage. The maximum effect is found seven months after testing, with an impact of approximately 1.4 percentage points, and it then begins to decline. The matching method shows a more rapid decline, but almost always within the confidence interval of the fixed effects regression. After 12 months, both estimates are statistically different from zero, at 1 to 1.2 percentage points.[11]

In terms of wages (including zeros for non-employment), at the time of testing and one month later, the effect is close to zero, but two months after testing the impact is more considerable and continues to grow. For example, six months after testing, the wages of those testing positive were approximately 6 percent higher than the wages of those testing negative, for both estimates. Like the employment estimates, the maximum effect in earnings is found seven months after testing, peaking at 7 percent. Then it declines slightly and finally increases again.

The positive effect on employment is driven mainly by low-income workers. Fig. 3 uses the matched sample to plot the percent employed by percentile of the pre-treatment wage distribution (as in Fig. 1). Those testing positive are in black and those testing negative are in gray. It is clear that at the bottom of the wage distribution, employment is higher at six or 12 months after the test for those who tested positive than for those who tested negative (panel A). However, beginning around the 40th percentile, there are no longer differences in the percentages for the two groups. Similarly, the gain in wages is driven mainly by low-income workers (panel B).[12]

Fig. 4 shows the estimates six and 12 months after the test for different sociodemographic groups, in order to analyze other potential heterogeneities, including the results for both matching and fixed effects regression. In general, the effects are similar for both methods. The employment effect is greater for men than for women, and it is greater for workers younger than 30 and between 45 and 60 than for those between 30 and 44. The effect for older workers is highly imprecise. The estimation by income decile shows that those workers with the largest increases in employment are at the bottom of the wage distribution, especially-six months after testing. For workers at the 40th percentile and above, the effect on employment is close to zero. Twelve months after testing the methods show a difference at the bottom of the distribution. The matching method estimates an effect that is close to zero for the first two deciles, while the fixed effects regression finds a positive impact. The effect on the third decile is positive and similar in both methods. The results for wages are comparable to those for employment.[13]

5. Discussion and conclusions

Our aim in this study was to estimate, using individual-level data, whether COVID-19 infections had an effect on labor market outcomes. Most of the research on the impact of the pandemic on the economy shows macro-level evidence. However, there are at least two reasons to believe that a COVID-19 infection may have harmful effects on workers at the individual level: the stigma and discrimination that may be directed at people who become infected (Sotgiu & Dobler, 2020), and the symptoms of long COVID that may reduce productivity or prevent people from returning to work (Garg et al., 2021).

We use a unique dataset that links administrative data for IMSS-registered workers to the results of tests for COVID-19 at IMSS facilities. With these data, we estimate the effect of testing positive for COVID-19 on labor market outcomes using both matching and fixed effects estimators. We find that, contrary to our working hypothesis, workers who tested positive for COVID-19 were more likely to keep their formal employment and had higher wages than those who tested negative. However, most of the estimated effects came from low-income workers.

Why is there a favorable employment effect for low-income workers who test positive for COVID-19? In Mexico, as in other less developed countries, provision of government-administered health care is contingent on whether the worker has formal employment. Low-income workers who test positive may value IMSS health care more or

[10] The difference in all lags with the matching method is close to zero and statistically insignificant at the 5 percent level. However, for the fixed effects regression at the 5 (1) percent level, there are marginally significant differences in two (zero) lags for employment and three (one) lags for wages. We control for previous labor market outcomes in the fixed effects regression, but not using lags in the regression produces similar results. Figures A1 and A2 show balance in the pretreatment period in terms of formal employment and wages, and Fig. A2 shows the event study for the full period. The confidence intervals in months 6–8 after testing do not intersect with any of the intervals in the pre-treatment period.

[11] One interpretation of the result is that COVID positive workers get medical leave. However, this effect would be larger in the first months after testing. As the effects are larger 6–12 months after testing, our interpretation is that they are likely driven more by workers` valuing a job with IMSS benefits or their uncertainty about the health consequences of getting COVID.

[12] The Supplementary Materials include a similar figure but using the wage distribution only for the treatment group and assigning the same distribution to the controls. The results are similar to the figure presented here.

[13] Figures A3-A6 and A8 show that results are robust to different matching methods. Fig. A9 assumes that thse who died continue to work in the period of analysis and it shows similar results as those presented here.

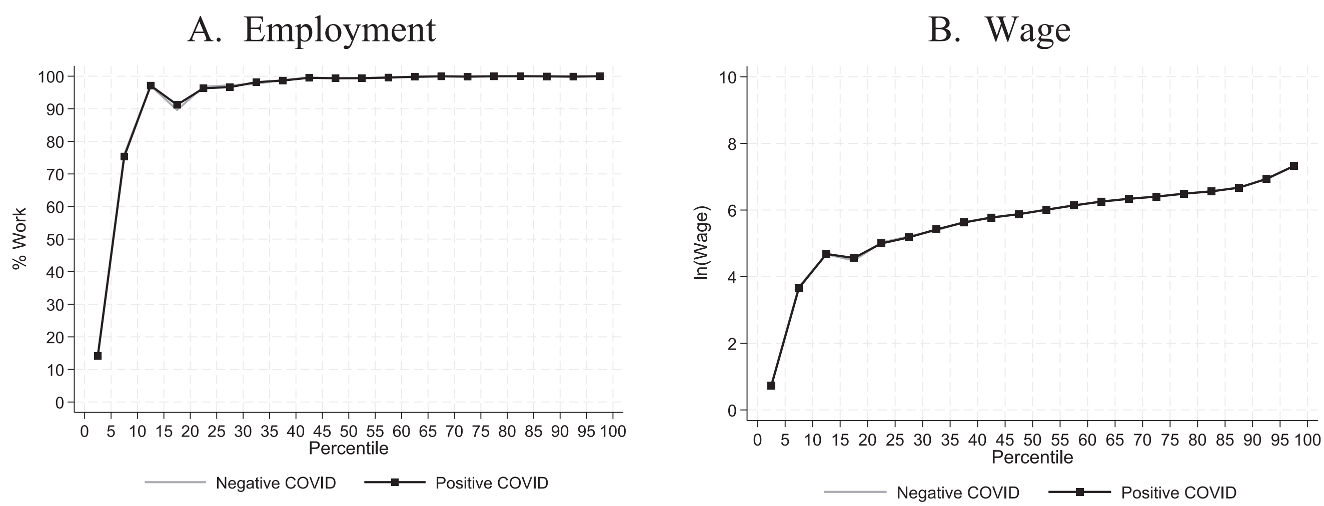

Fig. 1. Balance of previous employment and wages using the matched sample. Notes: Authors' calculations. The X-axis is ventiles of average earnings in the 12 months before the test. Panel A shows the proportion of months out of 12 the individual is formally employed before the test. Panel B is similar to Panel A, but shows earnings, using the natural logarithm of the wage plus one to include those with zero income.

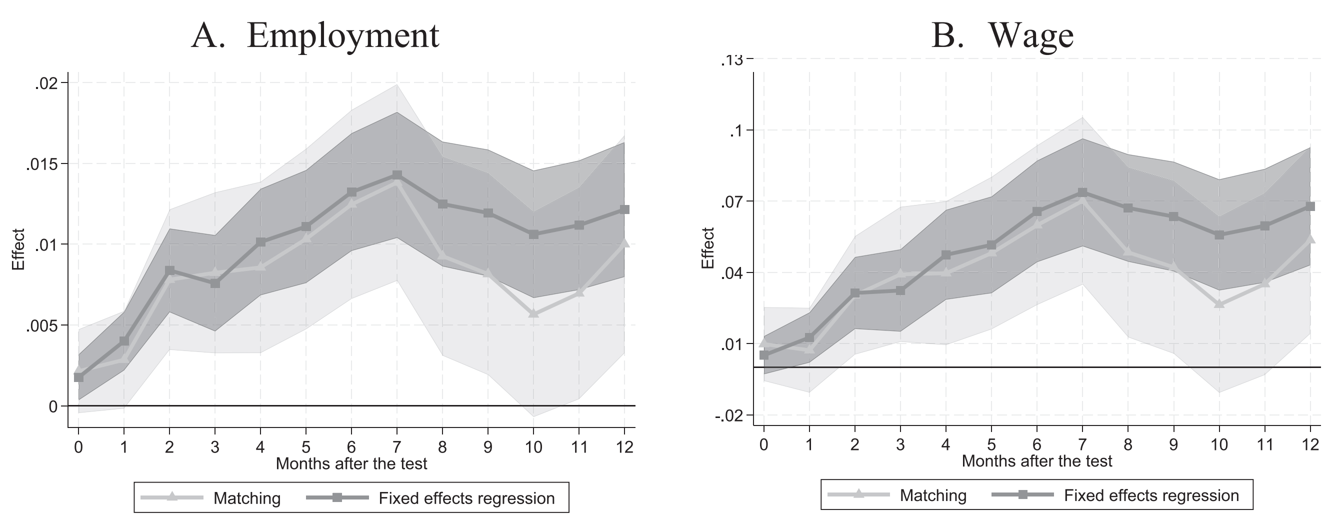

Fig. 2. Effects on employment and earnings of testing positive for COVID. Notes: Authors' calculations. Fixed effects regression with fixed effects groups by month of test, gender, age groups (younger than 30, 30–44, 45–59, and older than 60), number of jobs in the 12 months before the test, and ventiles of income using average earnings in the 12 months before the test. In addition, the regression controls for age, comorbidities, wage in each month before the test, and whether the individual is formally employed. The dependent variable in panel B is the natural logarithm of the wage plus one, to include zero earnings. The shading shows 95 percent confidence intervals, which are robust in the case of the fixed effects regression.

become more aware of its benefits for themselves and their families than those who have not been infected (especially if they received medical leave, a variable we do not observe in our dataset). They may also have more uncertainty about the effects of COVID on their future health. There is substantial evidence that COVID may cause long-term health issues (Domingo et al., 2021; Garg et al., 2021), which increases health care expenses and thus makes IMSS benefits more attractive. This higher valuation of healthcare services may increase attachment to formal employment (which is usually very low for low-income workers; see Fig. 1). Another possibility is that employers may believe that a worker who has already had COVID has immunity to the disease, or at least will not get severely ill if infected again, thus avoiding labor turnover. In any case, our results show that COVID-19 infections did not negatively affect workers' employment or earnings through discrimination or health mechanisms.

Of course, our analysis is only representative of formally employed private workers who were tested for COVID-19 at IMSS facilities in the period under analysis. This lack of generalizability makes it problematic to evaluate the situation of the informally employed population, whose access to health services is not conditional on work. The positive effect of COVID-19 infection on employment and wages does not necessarily hold among informal workers. However, the lack of an adverse impact of COVID infection on labor market outcomes is good news, since it suggests the absence of stigma or discrimination against infected workers. The findings also indicate that COVID-19 did not exacerbate inequalities in labor market outcomes, at least with respect to formally employed workers in the private sector.

CRediT authorship contribution statement

EO Arceo-Gomez: Conceptualization; Methodology; Formal analysis; Writing – Original Draft; Writing – Review & Editing. **RM Campos-Vazquez:** Conceptualization; Methodology; Formal analysis; Data Curation; Writing – Original Draft; Writing – Review & Editing. **G Esquivel:** Conceptualization; Methodology; Formal analysis; Writing – Original Draft. **E Alcaraz:** Conceptualization; Validation; Investigation;

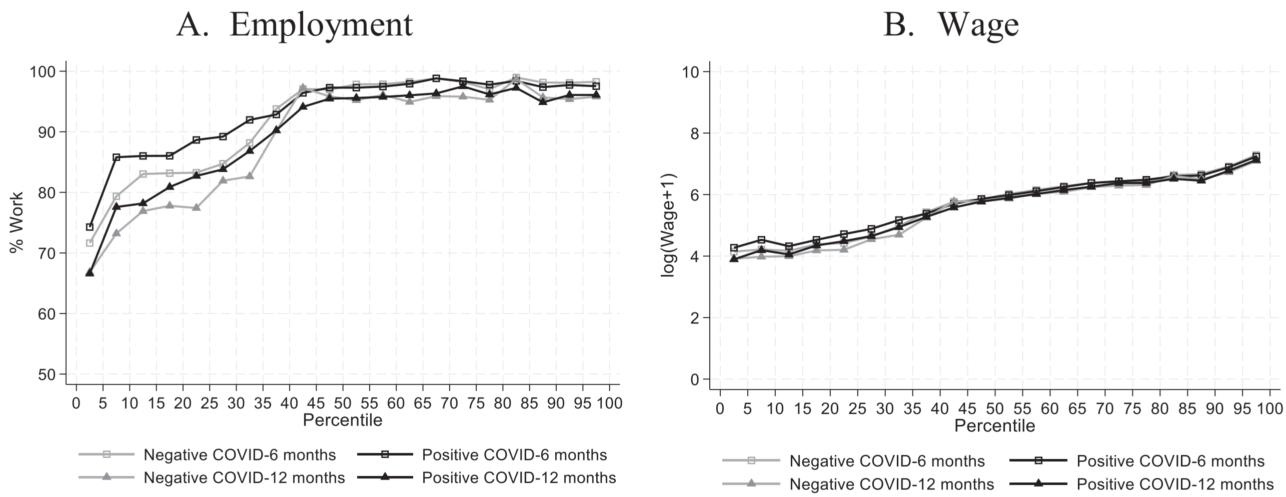

Fig. 3. Effects on employment and earnings by wage percentile of testing positive for COVID, at six and twelve months. Notes: Authors' calculations. The X-axis is ventiles of average earnings in the 12 months before the test. Panel A indicates whether the individual is formally employed. Panel B is similar to panel A, but shows earnings, using the natural logarithm of the wage plus one to include those with zero income. Outcomes are measured six and twelve months after the test.

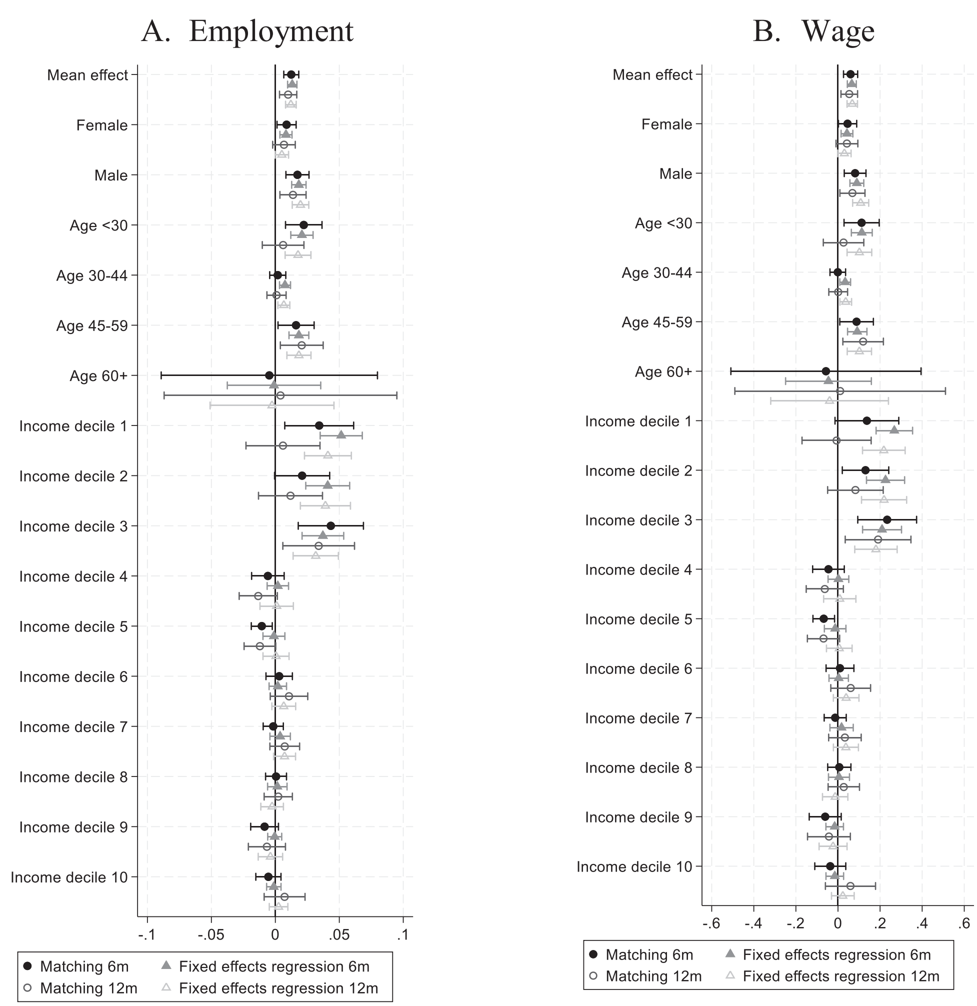

Fig. 4. Effects on employment and earnings of testing positive for COVID, by sociodemographic group. Notes: Authors' calculations. Gender and age groups are restricted in both the treatment and control groups. For the income decile estimates, the treatment group is matched to workers in the same decile and in adjacent deciles to avoid bad matches at the decile limits. Outcomes are measured six (6 m) and twelve (12 m) months after testing.

Resources; Supervision. **LA Martinez:** Data Curation; Validation; Investigation; Formal analysis. **NG Lopez:** Conceptualization; Validation; Investigation; Resources; Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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