How has labor demand been affected by the COVID-19 pandemic? Evidence from job ads in Mexico[1]

Raymundo M. Campos-Vazquez,[2] Gerardo Esquivel[3] and Raquel Y. Badillo[4]

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There is a concern among social scientists and policymakers that the COVID-19 crisis might permanently change the nature of work. We study how labor demand in Mexico has been affected during the pandemic by web scraping job ads from a leading job search website. As in the U.S., the number of vacancies in Mexico declined sharply during the lockdown (38 percent). In April there was a change in the composition of labor demand, and wages dropped across the board. By May, however, the wage distribution and the distribution of job ads by occupation returned to their pre-pandemic levels. Overall, there was a slight decline in specific requirements (gender and age), no change in required experience, and a temporary increase in demand for low-skilled workers. Contrary to expectations, opportunities for telecommuting diminished during the pandemic. Using a simple Oaxaca-Blinder decomposition, we find that the variation in the average advertised wage in April is explained more by a higher proportion of low-wage occupations than by a reduction in the wages paid for particular occupations. In sum, we find no evidence of a significant or permanent change in labor demand during the pandemic in Mexico.

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2 Professor at El Colegio de Mexico, on leave from the Banco de Mexico.
3 Banco de Mexico.
4 Banco de Mexico.

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1. Introduction

COVID-19 has substantially affected the economy in a very short period. Labor markets have been disrupted to an unprecedented extent. More than 20 million jobs were lost in the United States just in April 2020, a tripling of the unemployment rate in that month. In Mexico, the economically active population lost 12 million workers between March and April 2020, a decline of 21 percent. These dramatic changes may have effects on the labor market that are yet to be understood, especially on the behavior of potential employers, and there is a valid and growing concern about whether this shock will permanently affect the labor market. In this paper we analyze this question using data from job ads in Mexico before and during the pandemic.

It is possible that social distancing measures might permanently change the nature of work through a reallocation of jobs and changes in occupational structures (Baldwin, 2020). Delivery-oriented firms and essential sectors are growing, whereas sectors considered non-essential, such as tourism and transportation, are shrinking (Barrero, Bloom, & Davis, 2020). The future of work may be based on maintaining social distance, and it may depend on technology to communicate with and evaluate employees (Stahl, 2020). However, some authors have found that workers expect current work patterns to prevail (Von Gaudecker et al. 2020). It is therefore of the utmost importance to determine whether this crisis will cause a permanent adjustment to labor demand.

Traditional household surveys and administrative data provide ample information on workers' characteristics that can help us understand the effects of the crisis on labor supply. However, there is relatively little information about its effects on labor demand. Specifically, we know little about what types of jobs are still available or what new jobs are most in demand.

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An important source of data regarding labor demand is online job search websites. Web scraping and data science techniques make it possible to analyze the information included in these sites: types of vacancies, wages offered, job characteristics, and qualifications sought can be extracted and disentangled with the use of text analysis. Previous studies have analyzed the job search process (Faberman & Kudlyak, 2016) and the matching process between job seekers and vacancies (Choi, Banfi, & Villena-Roldan, 2019; Kuhn & Shen, 2013a; Marinescu & Rathelot, 2018). Others have focused on labor demand and hiring preferences, including the demand for specific skills and characteristics (Kuhn & Shen, 2015). There have also been studies focused on wages, which have found that the specification of compensation is strategic (Brenčič, 2012), and that wages are related to the wording used in job titles (Marinescu & Wolthoff, 2020). Other studies have analyzed how ads incorporate stereotypes of gender (Arceo-Gómez, Campos-Vázquez, Badillo-Salas, & López-Araiza, 2020) and have revealed the preferences of employers according to the characteristics of the job ads posted (Chowdhury et al. 2018; Kuhn & Shen, 2013b).

Online job boards have also allowed us to understand the labor market during crisis periods. Brown and Matsa (2016) study the matching process between job seekers and vacancies during the Great Recession in the U.S. They find that distressed firms attract fewer candidates and lower-quality applicants than non-distressed firms. Other studies focus on how skill requirements vary in times of economic crisis (Hershbein & Kahn, 2018; Modestino, Shoag, & Ballance, 2019), and find that skill requirements such as minimum education or experience increase when economic conditions worsen.

Forsythe, Kahn, Lange, and Wiczer (2020) analyze job search websites during the COVID crisis in the U.S. They have two key findings. First, job websites replicated the timing of unemployment insurance claims during the early stages of the COVID crisis,

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meaning that the information they contain is relevant at the macroeconomic level. Second, they find that employment vacancies declined by 30 percent in March 2020, and that all types of vacancies were affected, regardless of industry or occupation. For live tracking of the evolution of job postings, see Chetty et al. (2020).

Our paper contributes to this literature in several ways. First, there is scant evidence on how labor demand adjusts to a crisis in a developing country. Second, the crisis of the Great Confinement differs from the Great Recession. There is currently a debate about whether this crisis might permanently change the nature of work and labor demand, for example by favoring occupations with more options for telecommuting instead of face-to-face interaction. We provide some evidence against this possibility, at least in the early stages of the crisis. Third, we analyze the wage and occupational distribution of new job postings, as this distribution provides further evidence of possible changes in the labor market.

The COVID-19 pandemic has severely affected the labor market in Mexico in a very short time, mostly as a result of the measures to contain the virus. The first case in Mexico was diagnosed in late February. On March 14, the government suspended non-essential activities and rescheduled large public events. On March 23, the government announced a voluntary lockdown. These measures had an immediate impact on the labor market: in the last two weeks of March, Mexico lost more than 346,800 formal employees,[1] and the situation worsened in April, with a loss of more than 550,000 formal workers. The most affected sectors were personal services and construction, and more than 80 percent of those who lost their employment were in the lower part of the wage distribution (with earnings less than twice the minimum wage).

[1] https://elpais.com/economia/2020-04-08/mexico-pierde-en-dos-semanas-el-empleo-creado-en-2019-en-un-ambiente-de-tension-entre-el-gobierno-y-los-empresarios.html

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We obtained our data by web scraping the job ads from a leading job search website in Mexico.[2] We downloaded ads daily, beginning in January 2020. The period we analyze here is from January to July 2020. A typical ad includes the job title, the state in which the job is located, compensation, and the text of the ad. Companies use the text to describe the educational and skill requirements of the job, as well as some demographic requirements (age or sex). In total, we analyzed 254,605 ads.

The main results are as follows. We are not able to identify a fundamental change in the nature of work, only a decrease in the number of available jobs, which is expected given the lower level of economic activity. As in the U.S., the number of vacancies declined sharply with the beginning of mobility restrictions: there was a decline of 38 percent in the number of job ads between February and May 2020. Although there was a recovery in June and July, the number of job ads in those months was still 13 percent lower than in February. In April there was a temporary increase in demand in low-wage occupations and a decrease in high-wage occupations. That month, wages also dropped across the board. However, by May they had returned to their pre-pandemic levels. Using a simple Oaxaca-Blinder decomposition, we find that the decline in the average wage offered in April was mainly due to a larger share of low-wage occupations, rather than a change in the wages offered in given occupations. Finally, one might have expected that companies would maintain or increase labor demand for telecommuting jobs, but the data clearly rejects that option. The decline in this type of vacancy was more than proportional: their share of the total number of job ads fell from 51 percent in January-February to 45 percent in July. In sum, we do not find evidence of a permanent or significant change in the nature of work during this crisis in Mexico.

[2] For confidentiality reasons we do not reveal the website's name. However, it is among the top-5 job search websites in Mexico. See https://onaliat.mx/blog/index.php/las-5-mejores-plataformas-buscar-trabajo/.

2. Dataset

We construct the dataset using information from a leading Mexican online job search website. We web scrape the site daily from January to July 2020, for a total of 254,605 advertisements. The raw dataset contains the posting date, the job title, the description, the compensation offered, the location, and the economic sector of the hiring company. We also build other variables based on the textual description, including age, sex, education, and skills required. Finally, we classify the possibility of telecommuting, based on the work of Monroy-Gómez-Franco (2020).

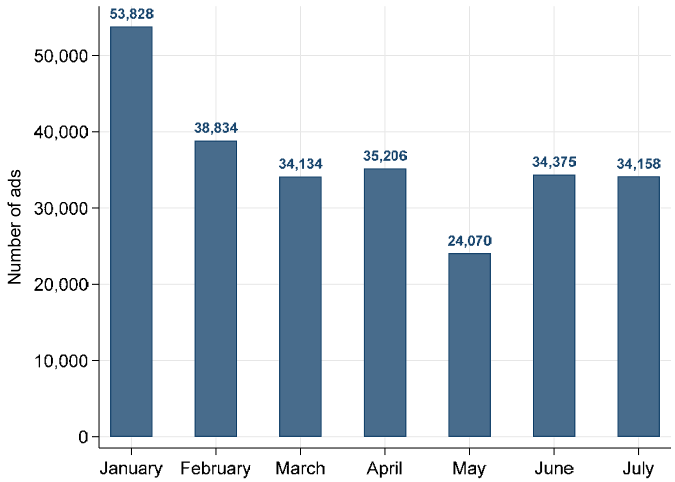
To construct the wage variable, we use text analysis of the information in the ad; where a range is specified, we take the mean value. We manually classify the job description according to the SINCO 2011 sector and subsector classifications of the Mexican National Institute of Statistics and Geography (INEGI) and the Mexican Ministry of Labor and Social Welfare (STPS). The advantages of these classifications are that they were especially designed for the Mexican labor market, and that they can easily be translated to other international classifications, such as the ISCO-08. This last point is important in following the methodology of Monroy-Gómez-Franco (2020) to classify telecommuting availability.

Other variables are obtained from terms regularly used in the job descriptions. The main objective of these categories is to understand the requirements for the jobs advertised. We classify these variables into three categories: sociodemographic variables, variables related to qualifications and benefits, and pandemic-related variables. Sociodemographic variables are characteristics such as gender, age, location, marital status, and education. Variables related to qualifications and benefits are based on the inclusion of words such as *commitment*, *punctual*, *honest*, *attentive*, *teamwork*, *helpful*, *courteous*, *control*, *initiative*, *motivation*, *pressure*, *proactive*, *responsible*, *enthusiasm*, *leadership*, *requests photograph*, *specifies appearance*, *English*, *common computer software*, *sales*, *customer*, *follow-up*, *availability*, *travel*, *driver's license*, *growth*, *development*, *training*, *bonus, benefits*, *and insurance*. Finally, the last category of variables is based on the inclusion of words related to the COVID-19 pandemic, such as *COVID*, *telecommuting*, *on-site work*, *distance*, and *health*.

3. Evolution and Distribution of Job Ads

Figure 1 shows the number of job ads in the sample. Usually the largest number of jobs are posted in January, advertisements decrease in February, and then they stabilize in subsequent months. From February to April there was a decline of 10 percent in the number of job ads, and from February to May the decline reached 38 percent. These reductions are larger than those found by Chetty et al. (2020) and Forsythe, Kahn, Lange, and Wiczer (2020) for the U.S. Although there is a recovery, the number of job ads in July is still 13 percent lower than in February.

Figure 1. Number of jobs advertised by month, Jan.-July 2020



Note: Authors' calculations.

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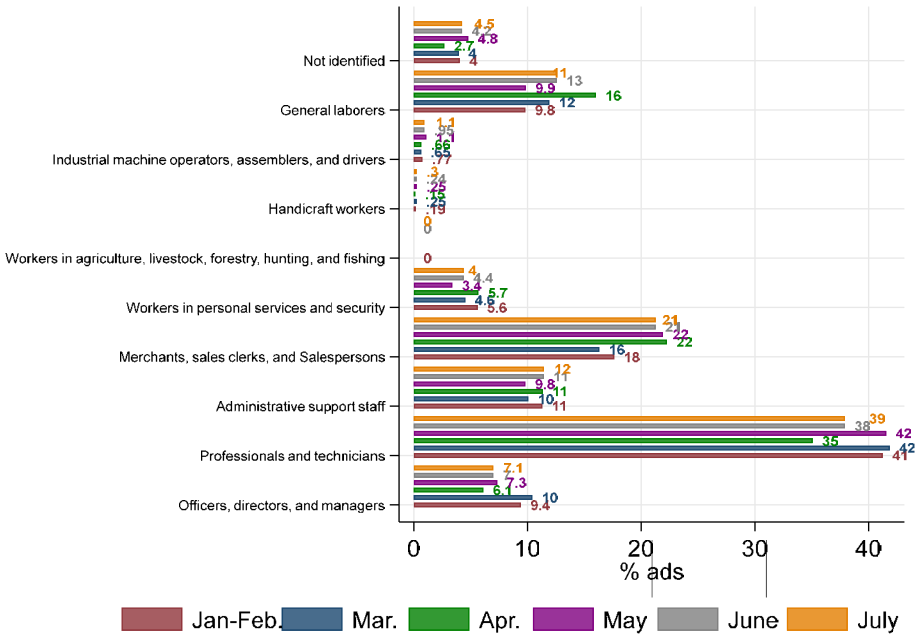
Figure 2 shows the distribution of job ads by occupation, codified at the one-digit level using the SINCO 2011 classification. Internet job searches in Mexico are biased toward higher-paying occupations. The 2019 Labor Force Survey indicates an average monthly wage of MXN $6,600, while the average in the sample for January and February is MXN $13,445. The occupational category with the highest demand (41 percent of the total ads in January-February) is professionals and technicians.

Figure 2. Distribution of job ads by occupation



Notes: Authors' calculations. Occupations are defined by SINCO 2011 classification at the one-digit level: officers, directors, and managers (SINCO 2011=1); professionals and technicians (SINCO 2011=2); administrative support staff (SINCO 2011=3); merchants, sales clerks, and salespersons (SINCO 2011=4); workers in personal services and security (SINCO 2011=5); workers in agriculture, livestock, forestry, hunting, and fishing (SINCO 2011=6); handicraft workers (SINCO 2011=7); industrial machine operators, assemblers, and drivers (SINCO2011=8); and general laborers (SINCO 2011=9).

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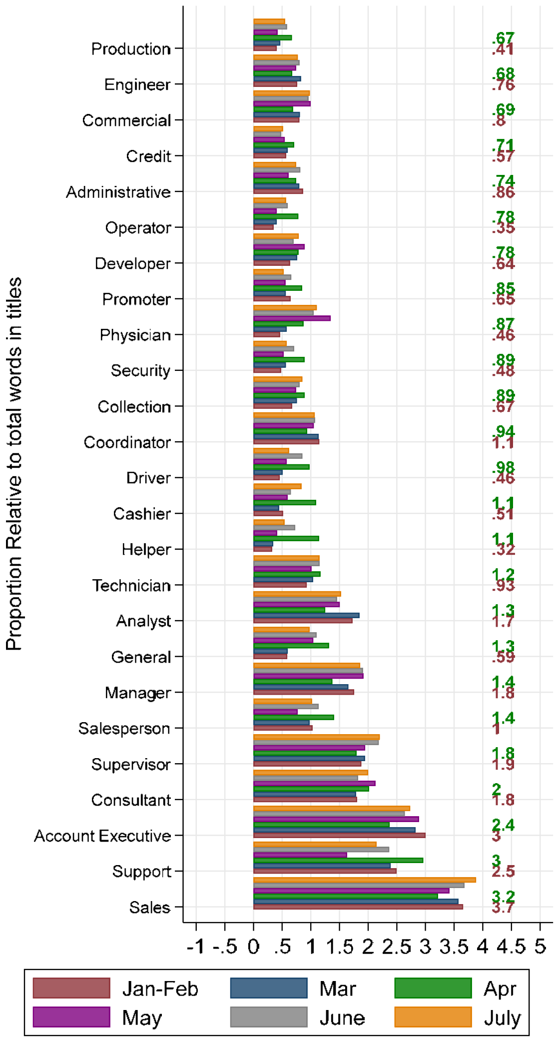
The figure shows the temporary shift in labor demand towards certain occupations. There is a pronounced spike in two occupations between January-February and April: merchants and sales personnel, and general laborers. Although voluntary confinement began in mid-March, there is no evidence of a clear shift in occupational targeting. Only during April does there appear to be a certain shift, but the distribution in June-July is very similar to that of January-February, except for an increase in the share of merchants and sales personnel, and small reductions in the demand for officers, directors, and managers, as well as for professionals and technicians.

Figure 3 shows changes in the frequency (relative to the total number of words) of the most common words in job titles. These 25 words represent 30 percent of the total number of words in job titles (not including stop words). The bars show the frequency of these words for each month, with the values for January-February shown on the right in brown and those for April in green. The figure shows that jobs related to sales, support, and account executives are in greatest demand. By April, there was a substantial increase in the frequency of job titles with the words *support*, *salesperson*, *general* (usually referring to general laborers), *technician*, *helper*, *cashier*, *driver*, *security*, *physician*, and *operator*. Many of these words returned to their January-February values by June-July, except for *physician,* which continued to increase, and for *general* and *cashier*, that remain slightly above their January-February levels.

Intuitively, based on Figure 3, it seems that there was a decline in the demand in April for the best paid managerial and professional jobs, but increased demand for low-paid general labor, operations, and support jobs, and in general a return to the January-February levels in May.

Figure 3. Most repeated words in job titles



Notes: Authors' calculations. The table shows the most frequent words relative to the total number of words in job titles, omitting stop words. To calculate the proportions, we grouped together words with different endings for gender (e.g., *vendedor/vendedora*) and number (i.e., plural vs. singular). The figures on the right indicate the proportion in January-February (brown) and in April (green).

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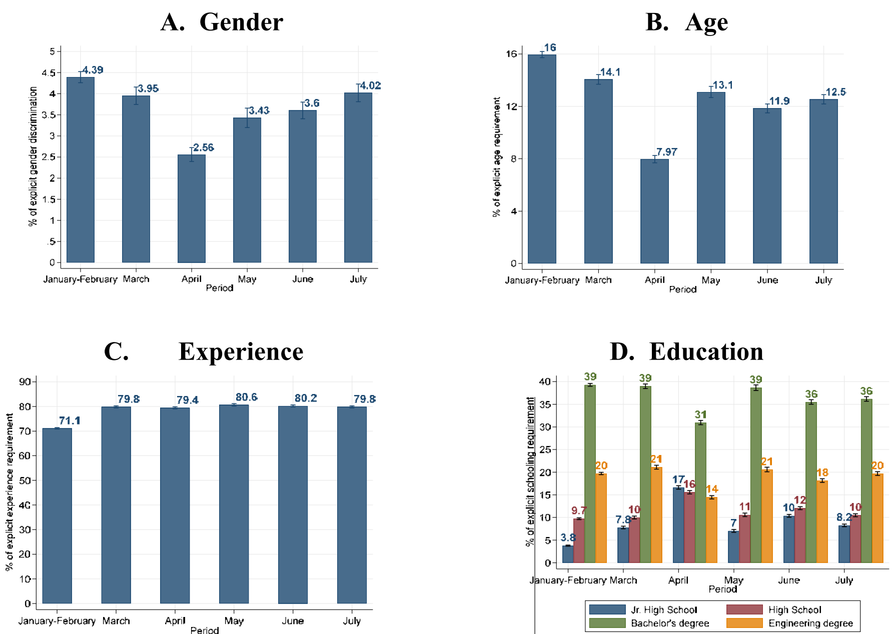
4. Change in Job Requirements During the Pandemic

If labor demand is shifting rapidly, and there is a greater need to hire people, we might expect to see a decline in specific job requirements. Alternatively, if the labor market tightens, we might expect to see an increase in certain requirements, such as experience or education. We calculate the proportion of job ads that specify gender, age, experience, or educational requirements (Figure 4).

Figure 4. Proportion of job ads that include specific requirements



Notes: Authors' calculations. Range plot shows the IC at 95 percent.

Panel A shows that there was a temporary reduction in ads specifying gender. From January to March, about 4 percent of job ads specified a gender, but in April this proportion fell to 2.5 percent. However, by July it had already returned to 4 percent. Panel B shows that there was a similar temporary decline in ads specifying age from March to April (from 14 to 8 percent), and then a rebound from May to July (from 8 to

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approximately 12.5 percent). These two panels combined suggest that labor demand changed significantly during April but that it returned to normal very quickly. The only change in requirements that seems to be more lasting is an increase in the demand for experience, which increased in March and has remained higher than its pre-pandemic level (panel C). This result is consistent with previous findings about stricter labor demand requirements in the context of an economic crisis (Hershbein & Kahn, 2018; Modestino, Shoag, & Ballance, 2019). Finally, the proportion of ads specifying educational requirements (panel D) shifted slightly in April but rapidly returned to its previous level: requests for bachelor's and engineering degrees declined in April while those for junior high and high school diplomas increased.

To better understand the requirements for different jobs, we analyze the use of selected words referring to skills, applicant characteristics, and criteria that could be related to the pandemic. Table 1 shows the percentage of ads that contain a word at least once, for the full sample and for specific occupations such as professionals, merchants, sales personnel, and general laborers, the occupations that have shown the largest change in demand during the pandemic.

Interestingly, characteristics like teamwork and commitment were in greater demand in April. The proportion of ads specifying teamwork increased from 15 percent in January-February to 31 percent in April but returned to the former value in May; in June and July, this specification increased again, to 22 percent. Ads specifying commitment increased from 5 percent in January-February to 13 percent in April; the proportion specifying this characteristic has remained higher than before the pandemic. Other requirements related to social interaction, such as being attentive, having a good appearance, including a photograph in the resume, and knowing English, fell during the first stage of the pandemic but soon returned to their previous levels, suggesting that there was no major shock for face-to-face jobs.

The specification of benefits also changed in April, with a decrease in ads using words such as *training*, *base wage*, and *commission*, but with an increase in the use of the word *benefits*. This could be related to the reduction in the average wage in April, with monetary or non-monetary benefits compensating for lower wages. However, since May these benefits-related words have slowly returned to their pre-pandemic levels.

Additionally, we explore some words related to the pandemic like *work at home*, *on-site*, *health*, *digital*, and *COVID*. Overall, we conclude that there are no large changes in the use of these words during the period studied. Using text analysis, we codify whether a job ad refers to *work at home*. There is an increase in the number of job ads using this term, particularly for professionals and technicians as well as for merchants, salesclerks, and salespersons, but the proportion of ads that use it is nonetheless relatively small (3 percent). There is also a small increase in the number of job ads using the term *work on site*. Thus, it seems that there has not been a substantial change in the option to work at home.

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Table 1. Specific requirements in job posts by occupation.

		All posts				Professional and Technicians				Merchants, Salesclerks & Salespersons				General laborers			
		Jan-Feb	April	May	June-July	Jan-Feb	April	May	June-July	Jan-Feb	April	May	June-July	Jan-Feb	April	May	June-July
Qualifications and Benefits	Observations	92,662	35,206	24,070	68,533	38,205	12,286	9999	26,423	16,333	7834	5274	14,486	9093	5640	2372	8192
	Commitment	5	13	6	8	4	9	5	6	4	16	7	9	8	19	8	14
	Punctual	6	6	5	6	6	5	5	6	6	6	5	5	6	9	5	8
	Honest	1	1	1	1	1	1	1	1	1	1	1	1	2	2	1	1
	Attentive	23	16	22	20	23	18	21	20	33	23	31	30	18	10	17	14
	Teamwork	15	31	17	22	14	25	15	19	11	31	14	21	18	42	22	31
	Helpful	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Courteous	1	0	1	1	1	0	0	1	0	0	0	1	1	0	1	0
	Control	18	16	21	20	21	19	22	23	9	9	12	11	12	7	12	12
	Initiative	3	2	3	3	3	2	3	3	3	2	2	3	2	1	2	2
	Pressure	9	5	8	8	10	6	9	9	7	4	7	7	7	3	6	5
	Proactive	8	5	8	7	8	5	7	7	8	6	10	9	5	2	5	4
	Responsible	11	8	12	11	11	8	11	11	10	7	12	9	10	6	12	8
	Motivated	38	30	43	44	33	24	29	32	77	56	85	84	36	37	47	36
	Leadership	7	9	8	9	7	10	8	9	7	8	8	9	6	7	8	7
	Requests photograph	4	2	3	3	3	2	3	3	5	2	3	4	2	1	2	1
	Specifies good appearance	11	6	10	10	9	5	7	7	18	9	16	16	7	2	6	5
	English	18	12	18	15	25	20	25	22	11	4	8	7	7	2	7	5
	Common computer software	12	7	12	11	15	11	15	14	7	3	6	6	5	2	4	4
	Sales	34	29	34	34	22	18	18	19	78	61	78	75	40	25	38	33
	Customer	41	44	42	42	35	37	34	34	64	68	66	68	44	42	45	43
	Follow-up	20	14	19	19	19	15	18	19	26	15	22	23	17	10	18	14
	Availability	3	2	3	3	3	2	3	2	4	2	3	3	2	2	3	2

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	Travel	6	7	7	7	6	7	6	7	8	7	7	9	5	7	8	7
	Growth	19	12	18	16	19	13	15	14	27	16	26	24	20	8	17	13
	Development	3	3	4	3	4	3	4	3	4	4	6	4	3	2	3	2
	Training	19	14	21	17	18	14	17	15	31	20	35	28	21	10	19	15
	Bonus	18	20	20	18	16	17	14	13	31	29	37	30	23	23	25	22
	Benefits	56	73	62	65	57	67	58	60	60	75	65	70	54	84	69	74
	Insurance	5	4	5	4	5	4	5	4	8	4	6	5	4	2	4	3
	Commissions	15	10	15	13	6	4	4	4	46	25	45	38	27	12	21	18
	Base Wage	29	20	30	27	28	24	28	26	46	23	43	38	32	16	30	23
Pandemic-related words	Work at home	1	2	3	3	1	2	4	4	1	2	4	3	0	0	1	0
	Work on site	1	1	2	2	1	1	1	1	2	1	3	2	1	0	1	0
	Work on site (in job title)	1	1	2	2	1	1	1	1	2	1	3	2	1	0	1	0
	Health	3	4	5	5	4	6	8	8	4	2	3	3	2	2	3	2
	Distance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Digital	3	3	5	4	4	4	6	5	3	2	5	4	1	0	1	1
	COVID	0	0	1	1	0	1	1	2	0	0	0	1	0	0	1	0

Note: Authors' calculations. See table S1 for words in Spanish. Each row indicates the percentage of ads that include the word in the first column at least once.

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5. Telecommuting

As noted, the COVID-19 crisis might change the nature of work by increasing the possibility of telecommuting. To account for this mechanism, we analyze the possibility for different occupations. Following Monroy-Gómez-Franco (2020), we match the SINCO 2011 classification to a pivotal classification (ISCO-08) and we then use the methodology of Dingel and Neiman (2020) to determine whether a particular job can be performed remotely. This methodology relies on the work context (such as email use and type of work) and the general activities involved in a job (such as physical activity, manipulation of objects, machines, or equipment, or personal contact with customers or the public). Like Monroy-Gómez-Franco (2020), we classify sales personnel in stores as not adaptable to telecommuting (ISCO-08=5521), because most Mexican stores do not have delivery services or computer systems. However, a disadvantage of this methodology is that the concept applies by its nature to occupations rather than individual jobs, and there may be heterogeneity within occupations in the demand for telecommuting.

Figure 5 shows the proportion of adaptability to telecommuting for different occupations. Anecdotal evidence indicates that there may be increased demand in adaptable occupations during the pandemic (Oppenheimer, 2020; Stahl, 2020). Baldwin (2020) goes even further by suggesting that the pandemic will increase demand for telemigrants, that is, workers working from abroad in countries with lower wages. However, compared to the first two months of 2020, the demand for such jobs in Mexico decreased by 11 percentage points in April and by 6 percentage points in May. This decrease is related to the increase in demand in April for workers in support activities, such as cashiers and drivers, and the decrease in professional activities adaptable to telecommuting. June and July show a similar proportion of telecommuting as in May. In

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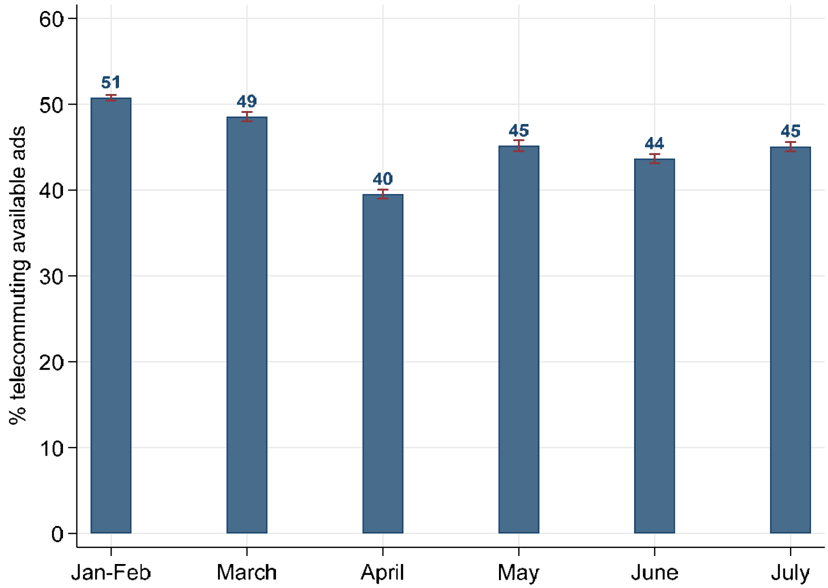
sum, there is thus far no empirical evidence that the nature of work is changing through an increase in demand for telecommuting.

Figure 6. Adaptability to telecommuting



Notes: Authors' calculations. Adaptability to telecommuting was calculated using the methodology of Monroy-Gómez-Franco (2020), including translation of the SINCO 2011 classification to O*NET to classify occupations, as in Dingel and Neiman (2020).

6. Change in Wages During the Pandemic

Table 2 presents the distribution of average monthly wages offered in job ads by month. The average monthly wage fell in April but increased in May. In April there was not only a drop in average wage, but also a shift in the overall distribution, as seen in the wages across different percentiles. This drop in wages is related to the type of jobs in demand. April saw a decrease in demand in the best-paid occupations, such as professionals and technicians, and an increase in demand for low-paid workers in support positions. The increase in wages observed in May is related to the increase in demand in

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higher-paid occupations. In June and July, the distribution of wages returned to the January-February level.

Table 2. Distribution of Average Monthly Wages, by Month

Period	Mean Wage (MXN)	10th Percentile	50th Percentile	90th Percentile	No. of Obs.
January	13,169 (13,067-13271)	4,697 (4,697-4,697)	9,394 (9,056-9,394)	26,304 (25,834-26,774)	53,495
February	13,827 (13,703-13952)	4,912 (4,725-5,146)	9,823 (9,823-10,151)	28,066 (27,599-28,066)	38,501
March	14,184 (14,049-14319)	4,680 (4,586-4,680)	10,296 (10,296-10,296)	28,080 (28,080-28,548)	33,908
April	12,332 (12,203-12460)	3,971 (3,971-4,078)	7,633 (7,565-7,943)	26,003 (26,003-26,476)	35,013
May	15,349 (15,179-15519)	4,710 (4,710-4,737)	11,303 (11,303-11,303)	30,614 (3,0614-32027)	23,958
June	13,965 (13,830-14,100)	4,684 (4,684-4,684)	9,603 (9,368-9,837)	28105 (28,105-28,112)	34,269
July	14,377 (14,233-14,520)	4,667 (4,667-4,667)	10,267 (10267-10,267)	28,466 (28,000-29,400)	34,088

Note: Authors' calculations. Wages in pesos (MXN) of 2018m7. 95% CI in parentheses, calculated using the binomial method.

To analyze the change across the full distribution we plot wage growth with respect to January-February by decile and month for the period April-July. Figure 7 shows the deciles for each month and the difference in average wage by decile. As seen in Table 2, the wage patterns are very different during April and May. In April, there is a decline in the average wage for each decile with respect to January-February: the wage distribution shifted to the left. By May, however, the pattern is reversed: there is wage growth in all deciles except the second one. The numbers for June and July reveal moderate increases in offered wages along most of the distribution. This figure is

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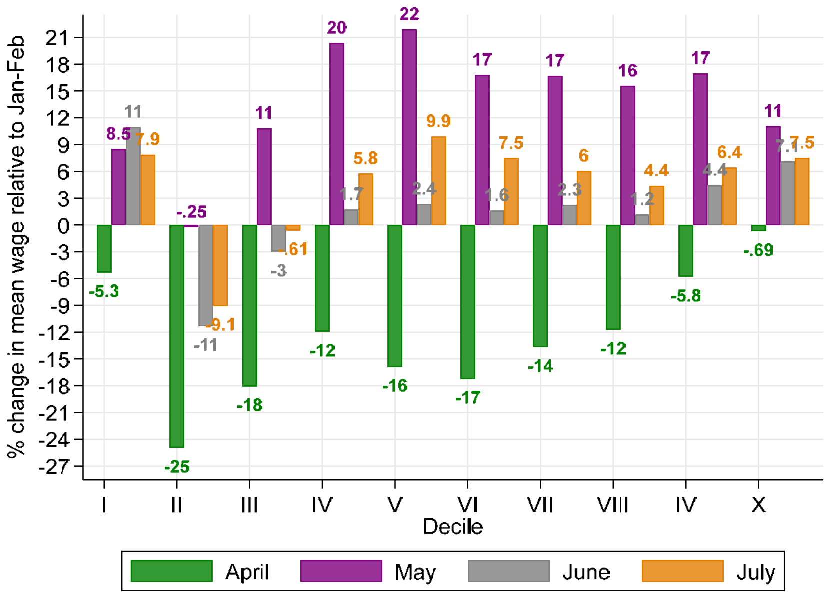
consistent with a temporary and significant change in labor demand during April that is quickly reversed in subsequent months.

Figure 7. Change in wages by decile with respect to January-February



Notes: Authors' calculations. Deciles are calculated for each month and then the average monthly wage is calculated within each decile.

Finally, we implement a simple Oaxaca-Blinder decomposition to investigate what is behind the abrupt change in wages during April and May. The Oaxaca-Blinder decomposition helps to understand whether the change in average wage is due to a shift in the proportion of occupations in demand or to a change in wages within occupations. This decomposition consists in estimating two OLS regressions, one for the period January-February and the other for each month. The independent variables are occupation dummies. If coefficients are stable across months, the Explained component should not change that much. On the other hand, if the Unexplained component grows, it means the premium for each occupation is gaining in relevance.

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Table 3 presents the results for the Oaxaca-Blinder decomposition with respect to January and February. The first rows indicate the average (log) wage of each month. April was the month most affected. The gap was 0.04 in March, but by April it decreased to -0.13 (log points). However, by June and July it had largely recovered. The Explained component row indicates the share of the total differential explained by the characteristics. This explained component proportion is very stable with the exception only of July, when it grows. This implies that the variation in wages observed throughout the period is mainly due to a change in demand for occupations and not a change in wages within occupations. For the specific case of the significant reduction in the average advertised wage in April, this result implies that it is due to a higher proportion of job ads for low-wage occupations than by a reduction in the wages paid for given occupations.

Table 3. Oaxaca-Blinder Decomposition

	March	April	May	June	July
Differential					
Current month	9.29	9.11	9.36	9.26	9.29
	[.002]	[.0022]	[.0023]	[.002]	[.0019]
January-February	9.24	9.24	9.24	9.24	9.24
	[.0011]	[.0011]	[.0011]	[.0011]	[.0011]
Difference current month vs. Jan-Feb	0.04	-0.13	0.12	0.02	0.05
	[.0022]	[.0024]	[.0026]	[.0023]	[.0022]
Decomposition					
% Explained	0.31	0.29	0.32	0.30	0.46
% Unexplained	0.69	0.71	0.68	0.70	0.54
Observations in current month	32,566	34,074	22,810	32,812	32,561
Observations in Jan-Feb	88,267	88,267	88,267	88,267	88,267
Total number of observations	120,833	122,341	111,077	121,079	120,828

Notes: Authors' calculations. Standard errors in brackets.

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7. Conclusions

The COVID-19 crisis has had a major impact on the economy and the labor market. As a result, there are valid concerns that this crisis might permanently change the nature of work. Using job ads from a leading job search website in Mexico, we show that there is no evidence thus far to support this concern. We download 254,605 ads from January to July 2020 and analyze the jobs advertised and the posted wages, and we use text analysis to analyze the skills and personal characteristics sought.

We find that there is a decline in the number of job advertisements, but that there is no structural change in labor demand. As in the U.S. (Chetty et al. 2020; Forsythe, Kahn, Lange, & Wiczer 2020), the number of vacancies declined sharply in the early stages of the pandemic (around 38 percent) due to the implementation of mobility restrictions. By July, the number of vacancies had partially recovered, and it was only 13 percent less than at the beginning of the year. Most importantly, however, the structure of labor demand changed only temporarily: there was greater demand for low-wage occupations and workers with low educational levels in April, but from May to July demand was back to pre-pandemic levels. The possibilities offered for telecommuting did not increase in this period. The skills and personal characteristics sought did not fundamentally change during the period.

Future research should continue to monitor the behavior of labor demand. Qualitative and case studies are also necessary to investigate changes in the nature of work within occupations and within firms. It is plausible that job ads and aggregate data on employment do not account for small changes in the employer-employee relationship. These small changes might be the causal mechanism that explains structural changes in the nature of work that might occur in the future.

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References

Arceo-Gómez, E. O., Campos-Vázquez, R. M., Badillo-Salas, R. Y., & López-Araiza, S. (2020). *Gender Stereotypes in Job Advertisements: What Do they Imply for the Gender Salary Gap?* Mexico. Retrieved from http://conference.iza.org/conference_files/DATA_2020/campos%20vazquez_r4830.pdf

Baldwin, R. E. (2020). Covid, hysteresis, and the future of work. https://voxeu.org/article/covid-hysteresis-and-future-work

Barrero, J. M., Bloom, N., & Davis, S. (2020). COVID-19 Is Also a Reallocation Shock. National Bureau of Economic Research (NBER) Working Papers (No. 27137). https://doi.org/10.3386/w27137

Brenčič, V. (2012). Wage posting: evidence from job ads. *Canadian Journal of Economics/Revue Canadienne d'économique*, *45*(4), 1529–1559. https://doi.org/10.1111/j.1540-5982.2012.01738.x

Brown, J., & Matsa, D. A. (2016). Boarding a Sinking Ship? An Investigation of Job Applications to Distressed Firms. *The Journal of Finance*, *71*(2), 507–550. https://doi.org/10.1111/jofi.12367

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., & the Opportunity Insights Team. (2020). *How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data.* Retrieved from https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf

Choi, S., Banfi, S., & Villena-Roldan, B. (2019). Sorting On-Line and On-Time. Social Sciencie Research Network (SSRN) Electronic Journal (No. 3323068).

https://doi.org/10.2139/ssrn.3323068

Chowdhury, A. R., Areias, A. C., Imaizumi, S., Nomura, S., & Yamauchi, F. (2018). *Reflections of Employers' Gender Preferences in Job Ads in India: An Analysis of Online Job Portal Data*. The World Bank. Policy Research Working Papers (No. 8379). https://doi.org/10.1596/1813-9450-8379

Dingel, J., and B. Neiman. (2020). How Many Jobs Can be Done at Home? *Covid Economics: Vetted and Real-Time Papers* 1: 16-24. https://cepr.org/sites/default/files/CovidEconomics1.pdf.

Faberman, J. R., & Kudlyak, M. (2016). What Does Online Job Search Tell Us about the Labor Market? *Economic Perspectives*, *40*(1), 15. Retrieved from https://www.chicagofed.org/publications/economic-perspectives/2016/1-faberman-kudlyak

Forsythe, E., Kahn, L. B., Lange, F., & Wiczer, D. G. (2020). Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims. National Bureau of Economic Research (NBER) Working Papers (No. 27061). https://doi.org/10.1017/CBO9781107415324.004

Hershbein, B., & Kahn, L. B. (2018). Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings. *American Economic Review*, *108*(7), 1737–1772. https://doi.org/10.1257/aer.20161570

Kuhn, P., & Shen, K. (2013a). Do Chinese Employers Avoid Hiring Overqualified Workers? Evidence from an Internet Job Board. *Research in Labor Economics*: *Vol. 37*. *Labor Market Issues in China* (pp. 1–30). https://doi.org/doi:10.1108/S0147-9121(2013)0000037005

Kuhn, P., & Shen, K. (2013b). Gender Discrimination in Job Ads: Evidence from China.

Covid Economics 46, 1 September 2020: 94-122

The Quarterly Journal of Economics, *128*(1), 287–336. https://doi.org/10.1093/qje/qjs046

Kuhn, P., & Shen, K. (2015). Do employers prefer migrant workers? Evidence from a Chinese job board. *IZA Journal of Labor Economics*, *4*(1), 22. https://doi.org/10.1186/s40172-015-0038-0

Marinescu, I., & Rathelot, R. (2018). Mismatch Unemployment and the Geography of Job Search. *American Economic Journal: Macroeconomics*, *10*(3), 42–70. https://doi.org/10.1257/mac.20160312

Marinescu, I., & Wolthoff, R. (2020). Opening the Black Box of the Matching Function: The Power of Words. *Journal of Labor Economics*, *38*(2), 535–568. https://doi.org/10.1086/705903

Modestino, A. S., Shoag, D., & Ballance, J. (2019). Upskilling: Do Employers Demand Greater Skill When Workers are Plentiful? *The Review of Economics and Statistics*, *0*, 1–46. https://doi.org/10.1162/rest_a_00835

Monroy-Gómez-Franco, Luis. (2020). ¿Quién Puede Trabajar Desde Casa ? Evidencia Desde México. Documento de trabajo Centro de Estudios Espinoza Yglesias (CEEY) (No. 06 / 2020). Retrieved from: https://ceey.org.mx/wp-content/uploads/2020/05/06-Monroy-Gómez-Franco-2020.pdf.

Oppenheimer, A. (2020). El trabajo, después del Covid-19. *La Nación*. Retrieved from https://www.lanacion.com.ar/opinion/el-trabajo-despues-del-covid-19-nid2381283

Stahl, A. (2020). What Does Covid-19 Mean For the Future of Work. *Forbes*. Retrieved from https://www.forbes.com/sites/ashleystahl/2020/06/15/what-does-covid-19-mean-for-the-future-of-work/#5c8a0efa446f

Von Gaudecker, H.-M., Holler, R., Janys, L., Siflinger, B., & Zimpelmann, C. (2020).

Covid Economics 46, 1 September 2020: 94-122

Labour supply in the early stages of the CoViD-19 Pandemic: Empirical Evidence on hours, home office, and expectations. IZA Institute of Labor Economics. Discussion Paper Series (No. 13158). Retrieved from http://ftp.iza.org/dp13158.pdf

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Supplementary Material

Table S1: Translation of Words in Table 2

	Words: English	Spanish
Qualifications and Benefits	Commitment	Compromiso
	Punctual	Puntual
	Honest	Honesto
	Attentive	Atento
	Teamwork	Trabajo en Equipo
	Helpful	Servicial
	Courteous	Amable
	Control	Control
	Initiative	Iniciativa
	Pressure	Presión
	Proactive	Proactivo
	Responsible	Responsable
	Motivated	Motivado
	Leadership	Liderazgo
	Requests photograph	Foto
	Specifies good appearance	Presentación
	English	Inglés
	Common computer software	Software
	Sales	Ventas
	Customer	Cliente
	Follow-up	Seguimiento
	Availability	Disponibilidad de tiempo
	Travel	Viajar
	Growth	Crecimiento
	Development	Desarrollo
	Training	Capacitación
	Bonus	Bono
	Benefits	Prestaciones
	Insurance	Seguro
	Commissions	Comisiones
	Base wage	Salario Base
Pandemic-related words	Work at home	Trabajo en Casa
	Work on site	Trabajo Presencial
	Work on site (in job title)	Trabajo Presencial (en el título del empleo)
	Health	Salud
	Distance	Distancia
	Digital	Digital
	COVID	Covid

Table S2. Occupations translation in Figure 4

English	Spanish
Officers, directors and managers	Funcionarios, directores y jefes
Professionals and technicians	Profesionistas y técnicos
Administrative support staff	Trabajadores auxiliares en actividades administrativas
Merchants, salesclerks, and salespersons	Comerciantes, empleados en ventas y agentes de ventas
Workers in personal services and security	Trabajadores en servicios personales y vigilancia
Workers in agriculture, livestock, forestry, hunting, fishing	Trabajadores en actividades agrícolas, ganaderas, forestales, caza y pesca
Handicraft workers	Trabajadores artesanales
Industrial machine operators, assemblers, and drivers	Operadores de maquinaria industrial, ensambladores, choferes y conductores de transporte
General laborers	Trabajadores en actividades elementales y de apoyo

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Table S3. Most Frequent Words in Figure 5

English	Spanish
Engineer	Ingeniero
Commercial	Comercial
Supervisor	Jefe
Credit	Crédito
Administrative	Administrativo
Developer	Desarrollador
Operator	Operador
Promoter	Promotor
Physician	Medico
Collection	Cobranza
Security	Seguridad
Coordinator	Coordinador
Driver	Chofer
Supervisor	Supervisor
Cashier	Cajero
Helper	Ayudante
Technician	Técnico
Analyst	Analista
General	General
Manager	Gerente
Salesperson	Vendedor
Consultant	Asesor
Account Executive	Ejecutivo
Support	Auxiliar
Sales	Ventas
Production	Producción

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Table S4. Effect of occupations on Wage (OLS)

	Jan-Feb	March	April	May	June	July
Officers, directors, and managers						
Professionals and technicians	-0.12	-0.02	-0.20	-0.22	-0.15	-0.14
	[.0088]	[.014]	[.019]	[.019]	[.016]	[.016]
Administrative support staff	-0.52	-0.46	-0.72	-0.73	-0.67	-0.64
	[.0096]	[.016]	[.019]	[.021]	[.017]	[.017]
Merchants, Salesclerks and Salesperson	-0.35	-0.26	-0.70	-0.54	-0.52	-0.46
	[.0095]	[.016]	[.019]	[.02]	[.017]	[.017]
Workers in personal services and security	-0.60	-0.47	-0.76	-0.57	-0.60	-0.63
	[.012]	[.022]	[.023]	[.033]	[.025]	[.029]
Workers in agriculture, livestock, forestry, hunting, fishing	-0.24					
	[.18]	[.]	[.]	[.]	[.]	[.]
Handicraft workers	0.15	0.21	0.01	-0.31	-0.71	-0.24
	[.051]	[.076]	[.073]	[.064]	[.015]	[.11]
Industrial machine operators, assemblers, and drivers	-0.09	0.00	-0.26	-0.18	-0.15	-0.12
	[.027]	[.046]	[.048]	[.055]	[.073]	[.058]
General laborers	-0.49	-0.52	-0.81	-0.71	-0.11	-0.23
	[.01]	[.016]	[.019]	[.022]	[.045]	[.039]
Constant	9.51	9.47	9.61	9.75	-0.70	-0.65
	[.008]	[.013]	[.017]	[.018]	[.017]	[.018]
Number of observations	88267	32566	34074	22810	32812	32561
R^2 adjusted	0.08	0.08	0.16	0.11	0.13	0.11

Note: Authors' calculations. Dependent variable ln(wage), robust standard errors showed in brackets