

Job referrals, minimum wage and labor market outcomes

*Danilo Aristizabal*¹

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Abstract

Despite their documented importance in the labor market, little is known about how salaried workers use job referrals to find their jobs and their correlation with wages in developing countries. This paper contributes to the literature of job referrals and labor market outcomes showing that job referrals pay a premium or penalty to workers depending on whether the minimum wage is binding or not. I show that in Mexico where the median wage is 40% the minimum wage, salaried workers who used job referrals as the principal way to get their current job report earning higher wages than salaried workers who used other methods of search. In contrast, in Colombia where the median wage is 90% the minimum wage, workers who used job referrals as the principal search method have a wage penalty. This paper explores a mechanism to try to reconcile these two different stories. I argue that a possible reason for these different results is that workers use job referrals for different reasons, depending whether it is easy or hard to find employment.

(JEL: J31, J63, J64).

Keywords: Job referrals, minimum wage, worker's wage, unemployment duration, tenure, formal worker.

¹Universidad de los Andes. Email: de.aristizabal411@uniandes.edu.co

1. Introduction

Several studies show that at least one-third of employees have obtained their current job through family members or friends, pointing towards the importance of job referrals in the job search process (Granovetter 1995; Corcoran, Datcher, and Duncan 1980; Topa 2011; Hensvik and Nordström Skans 2013; Rodriguez-Villalobos and Rangel-González 2020; Ioannides and Datcher Loury 2004; Bewley 2021). However, it is not well established what are the implications of job referrals for labor market outcomes. While the theoretical literature has proposed some possible channels through which job referrals could play an important role in the match formation process, understanding the effects of job referrals has proven difficult, in large part because there are few representative data sets containing detailed information about the job search and hiring processes.

The existing empirical literature in developed economies has found conflicting evidence regarding the effect of job referrals on labor market outcomes (Marsden and Gorman 2001; Loury 2006; Pellizzari 2010; Brown, Setren, and Topa 2016; Lester, Rivers, and Topa 2021). In developing countries, such as India and Malawi, some authors have found that referral-based hiring has the potential to disadvantage qualified workers (Beaman and Magruder 2012; Beaman, Keleher, and Magruder 2018). In Colombia, Diaz (2009) shows that referrals increase the probability of finding a job, but in the informal sector, which reflects the prevalence of informal-sector jobs to be filled through this method rather than a causal effect. This last study also suggest there is a wage penalty in formal-sector firms for workers who used referrals to find a job compared to those who used other methods of search.

There are many reasons why workers may end up using referrals to get their jobs. One possible explanation is that workers use referrals to improve the match quality, reflected in earning higher wages compared to those who use other job search methods. Other possible explanation is that workers use job referrals because they have limited access to wage offers through other channels and as a result workers may rely on job referrals as a last resort. Labor market outcomes for workers with “limited choices” alternatives and for workers with “good matches” would be very different.

Economies with a high minimum wage usually make it harder for workers to find employment. When finding employment is hard, workers tend to accept first job offers which not necessarily are well paid matches. In this scenario, job referrals may impair, rather than enhance, the ability of some workers to find the highest possible pay job. In particular, workers that for their individual characteristics are more likely to earn wages near the minimum wage may end up using job referrals as a way to reduce unemployment duration rather than as a way to improve their match quality. On the other side, workers that for their individual characteristics are more probable to earn wages far above the minimum wage may end up using job referrals as a way to improve their match quality rather than reduce their unemployment duration.

This paper shows evidence that for a country with a high minimum wage, which makes it more difficult to find a job, referrals are a tool used for workers to reduce unemployment duration, while for a country with a relatively small minimum wage, job referrals are used to improve the match quality, reflected in higher wages.

The base model for the relationship between salary and the job search method was developed by Montgomery (1991). In his two-period model he assumes that in period 1 firms know the productivity of their employees, and in the period 2 there are two types of workers that can be employed: those hired by job referrals, and others hired using other search methods; in both cases the firm does not know the productivity of the hired person, therefore there is an adverse selection problem. In equilibrium, the firm offer a higher salary at the referral person, that is determined by the number of social networks she holds (Montgomery 1991). Montgomery's paper is focused on the effect of referrals on the productivity of the matches. Later, Simon and Warner (1992), developed a job matching model, where additionally to earn higher initial salary, the referred workers also display lower turnover than the non-referred workers, the reason for this is that referred workers have similar productivity with the current employees and their variance is lower compared with non-referred workers (Simon and Warner 1992). Calvo-Armengol and Jackson (2004) used probability functions and correlation coefficients and found that the outcomes on wages and duration of employment when using job referrals method depends on the structure of the network and the length of time the person was unemployed (Calvo-Armengol and Jackson 2004).

Cahuc and Fontaine (Cahuc and Fontaine 2009) developed a search model to understand when other search methods have an advantage over job referrals method. Pellizzari (2010) developed a search model for analyzing the impact on wages depending on the method used to find employment and he finds that the expected wage depends on the quality of job references, while Tumen (2016) indicated that the impact depends of peer effects and unobserved worker heterogeneity. This paper contributes to these literature showing that referrals have different correlation with labor market outcomes depending whether or not we are in a context with a high binding minimum wage.

This paper is organized as follows. Section 2 presents the data I use for Colombia and Mexico. Section 3 presents the regression analysis and results. Section 4 concludes.

2. Data

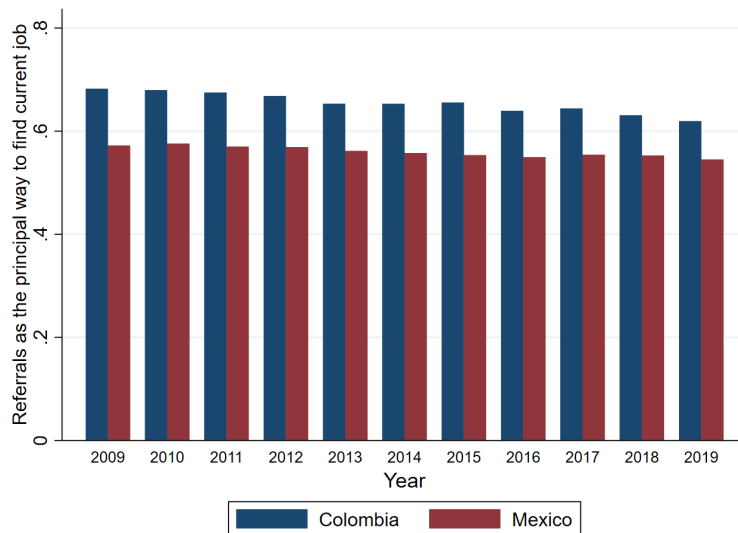
I use cross section household surveys for two developing countries which are very similar but differ in the minimum wage level: Colombia and Mexico. For the Colombian case I use the Colombian Household Survey (GEIH) and for the Mexican case I use the Mexican Household Survey (ENOE). I use the time period 2009-2019. The question I use to define whether a worker have used job

referrals as a principal way to find their job is *By what primary means did you get your current job?*. There are seven possible answers:

1. Asked for help from family, friends or colleagues.
2. Visited, brought, or sent resumes to businesses or employers.
3. Visited, took or sent resumes to employment exchanges or intermediaries.
4. Posted or consulted classified ads.
5. By calls
6. Through the public employment agency.
7. Another way

If the worker answer using help from family, friends or colleagues I classified that worker as using job referrals to get their job. If the answer is another one I classified them as using other methods as a principal way to find their current job. Most of the workers that answered this question are salaried workers, that is to say wage-earner workers, so I restrict the sample to only wage-earner workers. Figure 1 shows that the use of job referrals in Colombia and Mexico is very high, more than 50% of the wage-earner workers have used job referrals as the principal way to find their current jobs.

Figure 1. Job referrals use in Colombia and Mexico



Note: This figure shows the job referrals use from 2009 to 2019 for Colombia and Mexico.

Figures 2 and 3 show the distribution of log hourly earnings for Colombian and Mexican salaried workers. There are two things to point out from these graphs. First, Colombian minimum wage is highly binding, in other words, a considerable fraction of the Colombian salaried workers earn wages very near the minimum wage. In contrast, this does not appear to be the case in Mexico. Second, Colombian wage-earner workers who used job referrals to find their current job report lower earnings than non wage-earner workers who used other methods of search as the principal way to find their current jobs. The opposite is true for the Mexican workers, especially for the upper distribution of earnings.

Figure 2. Distribution of earnings of job referrals and non job referrals in Colombia

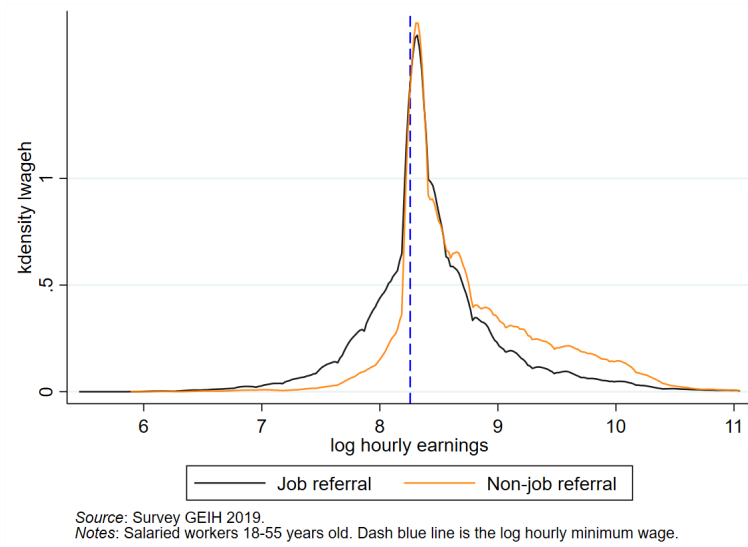
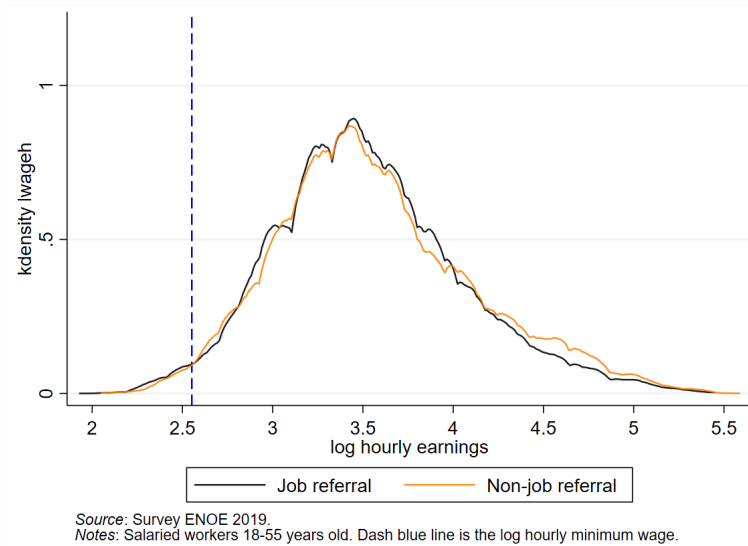
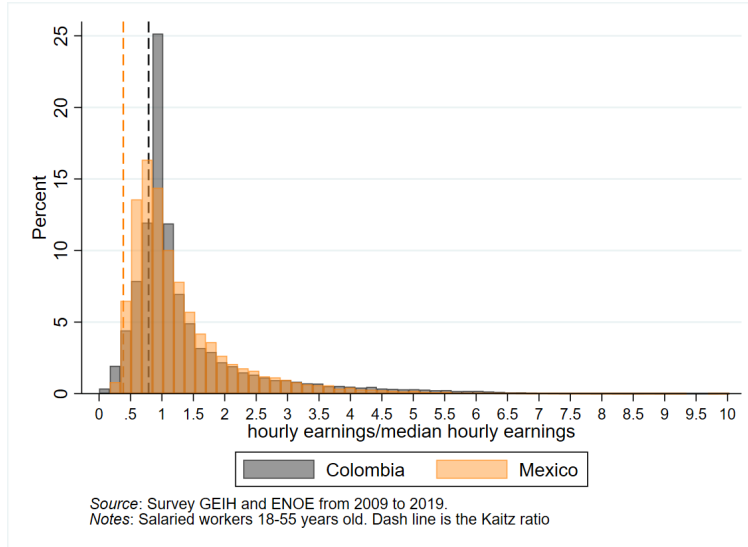


Figure 3. Distribution of earnings of job referrals and non job referrals in Mexico



In order to compare these two distribution of earnings I normalize them by the median wage within each country. Figure 4 shows both earning distributions normalized and also shows the kaitz ratio (KR)² for both countries. A high value of the KR, like that of Colombia, suggests a disproportionate minimum wage in relation to the other salaries in the economy, in other words, it means a very high minimum wage compared to the average productivity of workers. Colombian minimum wage is around 90% the median wage, while for the Mexican case, minimum wage is nearly 40% the median wage.

Figure 4. Distribution of earnings compared to the median wage in Colombia and Mexico



3. Regression analysis

3.1 Simple regression analysis

I restrict the sample to workers between 18 to 55 years old to only consider working age population.³ In order to understand which are the mechanisms that could help to explain how job referrals affect labor market outcomes we observe in the data, I start with the following simple regression analysis:

$$Y_{it} = \beta_0 + \beta_1 JR_{it} + \beta_2 X_{it} + \gamma_{rt} + u_{it} \quad (1)$$

- Y_{it} : Labor market outcome: Log hourly earnings of individual i in time t , tenure and firm size.

²The kaitz ratio is defined as: $kr = \frac{\text{minimumwage}}{\text{medianwage}}$

³Results are very similar using sample from 18 to 65 years old.

- JR_{it} : Dummy variable equal to one if individual i at time t report being employed using job referrals; 0 if i used other methods of search for their current job.
- X_{it} : Individual controls: Age, Age square, whether living with a partner, years of education, and gender.
- γ_{rt} : Time and area fixed effect.

I use Gelbach estimator to avoid sequence sensitivity when added covariates are intercorrelated (Gelbach 2016). Within the error term of equation (1) there are job characteristics that could be correlated with both JR_{it} and Y_{it} which would lead us to an endogeneity problem. However, since the objective is to see what type of job a job referral is helping to get, I decided not to control for job characteristics in these exercises, but instead use job characteristics as outcome variables (Angrist and Pischke 2009).

Tables 1 to 3 show the unconditional (column (1) and (4)) and conditional (column (2) and (5)) correlation between job referrals and labor market outcomes for Colombia and Mexico. Column 3 and 6 show the difference between the base and the full model, and it gives detailed information about which variables are explaining the differences we observe between the base and the full model. Table 1 shows that for the Colombian case, there is a wage penalty for workers who used job referrals as the principal way to find employment both unconditional and conditional on individual characteristics. In contrast for the Mexican case it seems there is an unconditional wage penalty but when we control for individual characteristics, there is a wage premium for those workers who used job referrals as the principal way to find employment. Variation in years of education explain most part of the wage difference.

Looking at other labor market outcomes, such as tenure and firm size, Tables 2 and 3 (columns 1 to 3) show that in Colombia wage-earner workers who used job referrals as the principal way to find employment compared to those who used other methods of job search have lower tenure and work in smaller firms. For the Mexican case, as it is also shown by Tables 2 and 3 (columns 4 to 6) wage-earner workers who used job referrals as the principal way to find employment compared to those who used other methods of job search have higher tenure and work in smaller firms. Again, variation in years of education seems to explain most part of the differences in the labor market outcomes for Colombian and Mexican salaried workers.

Why Colombian workers who used job referrals as a principal way to find employment seem to have a wage penalty while Mexican workers have a wage premium after controlling for individual characteristics? What differences in the labor market could explain the differences between the wages in the Colombian and Mexican contexts?

Table 1. Log hourly earnings and job referrals for Colombia and Mexico

Variables	Colombia			Mexico		
	(1) Base lwageh	(2) Full lwageh	(3) Explained lwageh	(4) Base lwageh	(5) Full lwageh	(6) Explained lwageh
Job referral	-0.2747*** (0.0207)	-0.0846*** (0.0164)	-0.1900*** (0.0131)	-0.0217*** (0.0017)	0.0330*** (0.0014)	-0.0546*** (0.0010)
Time	No	Yes	-0.0117*** (0.0015)	No	Yes	0.0004 (0.0002)
Area	No	Yes	0.0111** (0.0048)	No	Yes	-0.0010*** (0.0004)
Age	No	Yes	0.0103*** (0.0038)	No	Yes	0.0008** (0.0004)
Education	No	Yes	-0.1995*** (0.0138)	No	Yes	-0.0559*** (0.0008)
Men	No	Yes	-0.0001 (0.0008)	No	Yes	0.0009*** (0.0001)
Married	No	Yes	-0.0002 (0.0008)	No	Yes	0.0002* (0.0001)
Observations	1,255,894	1,255,803	1,255,803	489,745	489,745	489,745

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2. Tenure and job referrals for Colombia and Mexico

Variables	Colombia			Mexico		
	(1) Base Tenure	(2) Full Tenure	(3) Explained Tenure	(4) Base Tenure	(5) Full Tenure	(6) Explained Tenure
Job referral	-8.4254*** (1.6696)	-5.8517*** (0.8953)	-2.5766*** (0.9427)	0.0148 (0.0171)	0.0727*** (0.0152)	-0.0579*** (0.0086)
Time	No	Yes	0.2123*** (0.0181)	No	Yes	-0.0004 (0.0006)
Area	No	Yes	0.0287 (0.2619)	No	Yes	0.0123*** (0.0024)
Age	No	Yes	2.8516*** (0.6108)	No	Yes	0.0628*** (0.0077)
Education	No	Yes	-5.6432*** (0.4746)	No	Yes	-0.1413*** (0.0026)
Men	No	Yes	-0.0071 (0.0400)	No	Yes	0.0069*** (0.0008)
Married	No	Yes	-0.0189 (0.0990)	No	Yes	0.0018** (0.0007)
Observations	955,558	955,494	955,494	474,512	474,512	474,512

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Firm size and job referrals for Colombia and Mexico

Variables	Colombia			Mexico		
	(1) Base firm size	(2) Full firm size	(3) Explained firm size	(4) Base firm size	(5) Full firm size	(6) Explained firm size
Job referral	-2.1535*** (0.0964)	-1.7082*** (0.0808)	-0.4454*** (0.0242)	-0.7036*** (0.0072)	-0.5211*** (0.0068)	-0.1825*** (0.0031)
Time	No	Yes	0.0027*** (0.0007)	No	Yes	-0.0001 (0.0002)
Area	No	Yes	0.0354* (0.0186)	No	Yes	-0.0312*** (0.0016)
Age	No	Yes	-0.0003 (0.0024)	No	Yes	-0.0003 (0.0008)
Education	No	Yes	-0.4818*** (0.0277)	No	Yes	-0.1608*** (0.0024)
Men	No	Yes	-0.0006 (0.0063)	No	Yes	0.0093*** (0.0009)
Married	No	Yes	-0.0008 (0.0039)	No	Yes	0.0005* (0.0003)
Observations	1,255,894	1,255,803	1,255,803	489,745	489,745	489,745

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.2 Regression analysis around the minimum wage

Economies with high minimum wages make finding employment a more difficult task, basically because in these contexts there is higher unemployment and so there are more workers competing for the same jobs. As a result, economies where it is difficult to find employment might involve workers to use job referrals as a method to shorten unemployment duration rather than a way to improve the match quality.

To test whether having earnings near or far above the minimum wage have an impact on the labor market outcomes, I use the following exercise for workers whose earnings are around 90% and 110% of the minimum wage and for workers whose earnings are above 110% of the minimum wage:

$$Y_{it} = \beta_0 + \beta_1 JR_{it} + \beta_2 X_{it} + \gamma_{rt} + u_{it} \quad (2)$$

- Y_{it} : Labor market outcome: Log hourly earnings of individual i in time t .
- JR_{it} : Dummy variable equal to one if individual i at time t report being employed using job referrals; 0 if i used other methods of search for their current job.
- X_{it} : Individual controls: Age, Age square, whether living with a partner, years of education, and gender.

- γ_{rt} : Time and area fixed effect.

Tables 4 and 5 show the results of equation (2) for workers who are around and far above the minimum wage. There seems to be a wage penalty of 6% for workers who are around the minimum wage and used job referrals as the principal way to find their current job compared to those who used other methods of search, especially for the Colombian salaried workers. Variation in years of education explains 76% of the wage penalty. For wage-earner workers who are far above the minimum wage, it seems to be a wage premium of 3%, especially for the Mexican wage-earner workers. Again, variation in years of education seem to explain most of the difference between the base and the full model. Results are similar when I run these regressions around 20% and 5% of the minimum wage (see appendix).

Table 4. Log hourly earnings and job referrals around 10% of the minimum wage for Colombia and Mexico

Variables	Colombia			Mexico		
	(1) Base lwageh	(2) Full lwageh	(3) Explained lwageh	(4) Base lwageh	(5) Full lwageh	(6) Explained lwageh
Job referral	-0.1214*** (0.0012)	-0.0664*** (0.0010)	-0.0550*** (0.0005)	0.0061 (0.0048)	-0.0049** (0.0021)	0.0110** (0.0044)
Time	No	Yes	-0.0177*** (0.0004)	No	Yes	0.0102** (0.0043)
Area	No	Yes	-0.0007*** (0.0002)	No	Yes	0.0012** (0.0006)
Age	No	Yes	0.0051*** (0.0001)	No	Yes	-0.0002* (0.0001)
Education	No	Yes	-0.0420*** (0.0002)	No	Yes	-0.0001 (0.0001)
Men	No	Yes	0.0002*** (0.0001)	No	Yes	-0.0001 (0.0001)
Married	No	Yes	0.0001*** (0.0000)	No	Yes	0.0000 (0.0001)
Observations	1,059,045	1,058,953	1,058,953	10,766	10,766	10,766

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In sum, there is evidence that wage-earner workers who have earnings around the minimum wage seem to use job referrals as a way to improve match quality, measured in earning higher wages. Match quality does not only depend on wages. I plan to include other variables to measure match quality that can be captured by household surveys.

Since the way in which I determine who are around and who are far above the minimum wage depend on the actual earnings of the individual, there would be an endogenous problem when the

Table 5. Log hourly earnings and job referrals above 10% of the minimum wage for Colombia and Mexico

Variables	Colombia			Mexico		
	(1) Base lwageh	(2) Full lwageh	(3) Explained lwageh	(4) Base lwageh	(5) Full lwageh	(6) Explained lwageh
Job referral	-0.0848*** (0.0031)	0.0016 (0.0027)	-0.0864*** (0.0011)	-0.0229*** (0.0017)	0.0311*** (0.0014)	-0.0540*** (0.0010)
Time	No	Yes	-0.0113*** (0.0006)	No	Yes	0.0004 (0.0003)
Area	No	Yes	0.0131*** (0.0003)	No	Yes	-0.0007** (0.0003)
Age	No	Yes	0.0000 (0.0003)	No	Yes	0.0008** (0.0004)
Education	No	Yes	-0.0894*** (0.0008)	No	Yes	-0.0555*** (0.0008)
Men	No	Yes	0.0013*** (0.0001)	No	Yes	0.0008*** (0.0001)
Married	No	Yes	-0.0001 (0.0001)	No	Yes	0.0002* (0.0001)
Observations	300,703	300,701	300,701	478,636	478,636	478,636

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

dependent variable is the log hourly earnings. Right now I am working in simulating a wage for an individual based on individual characteristics to determine more exogenously who are around and who are far above the minimum wage.

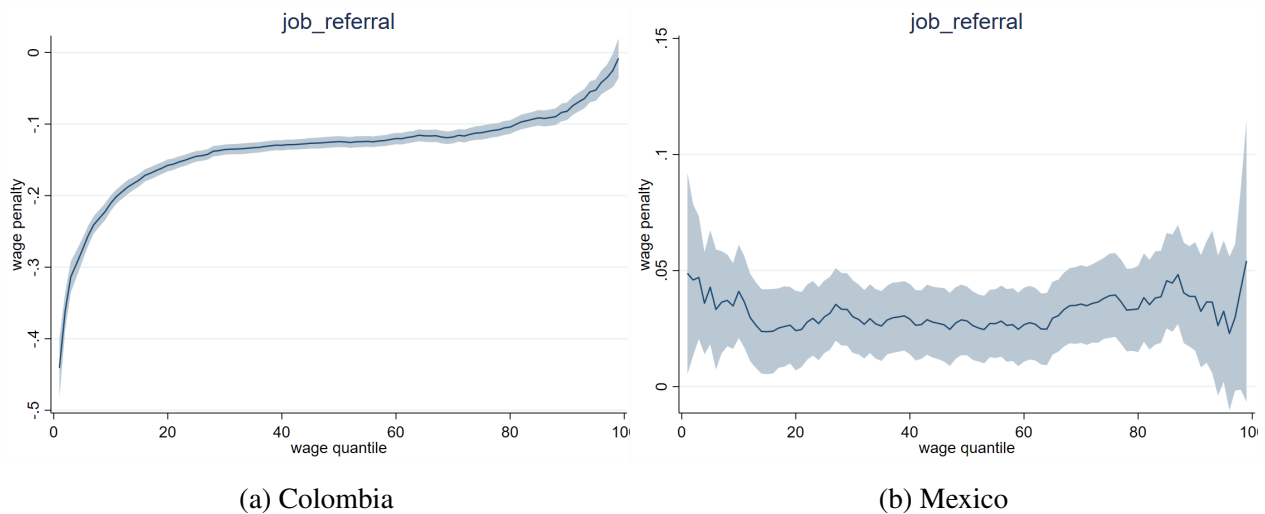
3.3 Quantile regression analysis

Finally, in order to see the impact of job referrals over all the distribution of wages, I use the following quantile regression:

$$Q_{\tau}(Y_{it}) = \beta_0(\tau) + \beta_1(\tau)JR_{it} + \beta_2(\tau)X_{it} + u_{it} \quad (3)$$

Figure 5 shows the results of the quantile regression when the dependent variable is log hourly earnings for the two different countries: (a) Colombia and (b) Mexico. Two things to highlight from these graphs. First, for the Colombian case, the wage penalty is decreasing as the wage quantiles are increasing, in other words wage penalty is higher for low quantiles while it is low for high quantiles of the wage distribution. Second, for the Mexican case, there is always a wage premium for all the distribution of wages, and it seems to be a little bit higher for the top wage distribution, after quantile 80.

Figure 5. Quantile regression for log hourly earnings



4. Conclusions

There are many reasons why salaried workers may end up using job referrals as the principal way to find a job. In this paper in particular we explore two different reasons: reduce unemployment duration or improve match quality. This paper shows suggestive evidence that in economies where it is difficult to find employment, job referrals impair, rather than enhance, the ability of some workers to find the highest possible job, which goes in the direction to show that salaried workers in contexts where it is difficult to find a job use job referrals not to improve match quality but to reduce unemployment duration.

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Appendix

Table A1. Log hourly earnings and job referrals around 20% of the minimum wage for Colombia and Mexico

Variables	Colombia			Mexico		
	(1) Base lwageh	(2) Full lwageh	(3) Explained lwageh	(4) Base lwageh	(5) Full lwageh	(6) Explained lwageh
Job referral	-0.2476*** (0.0016)	-0.1132*** (0.0014)	-0.1344*** (0.0006)	0.0110*** (0.0033)	-0.0020 (0.0018)	0.0130*** (0.0028)
Time	No	Yes	-0.0134*** (0.0003)	No	Yes	0.0113*** (0.0027)
Area	No	Yes	0.0035*** (0.0002)	No	Yes	0.0019*** (0.0005)
Age	No	Yes	0.0066*** (0.0002)	No	Yes	-0.0002*** (0.0001)
Education	No	Yes	-0.1312*** (0.0005)	No	Yes	-0.0001 (0.0001)
Men	No	Yes	0.0003*** (0.0001)	No	Yes	-0.0001* (0.0000)
Married	No	Yes	-0.0002*** (0.0000)	No	Yes	0.0001** (0.0000)
Observations	1,308,808	1,308,710	1,308,710	33,269	33,269	33,269

Robust standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table A2. Log hourly earnings and job referrals above 20% of the minimum wage for Colombia and Mexico

Variables	Colombia			Mexico		
	(1) Base lwageh	(2) Full lwageh	(3) Explained lwageh	(4) Base lwageh	(5) Full lwageh	(6) Explained lwageh
Job referral	0.0229*** (0.0046)	0.0303*** (0.0038)	-0.0074*** (0.0016)	-0.0254*** (0.0016)	0.0278*** (0.0013)	-0.0533*** (0.0010)
Time	No	Yes	-0.0119*** (0.0012)	No	Yes	0.0003 (0.0003)
Area	No	Yes	0.0224*** (0.0008)	No	Yes	0.0001 (0.0003)
Age	No	Yes	-0.0027*** (0.0002)	No	Yes	0.0006 (0.0004)
Education	No	Yes	-0.0160*** (0.0005)	No	Yes	-0.0551*** (0.0008)
Men	No	Yes	0.0006*** (0.0001)	No	Yes	0.0007*** (0.0001)
Married	No	Yes	0.0001 (0.0001)	No	Yes	0.0001 (0.0001)
Observations	81,307	81,307	81,307	456,471	456,471	456,471

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A3. Log hourly earnings and job referrals around 5% of the minimum wage for Colombia and Mexico

Variables	Colombia			Mexico		
	(1) Base lwageh	(2) Full lwageh	(3) Explained lwageh	(4) Base lwageh	(5) Full lwageh	(6) Explained lwageh
Job referral	-0.0703*** (0.0010)	-0.0397*** (0.0007)	-0.0306*** (0.0005)	0.0048 (0.0068)	-0.0031* (0.0018)	0.0079 (0.0066)
Time	No	Yes	-0.0185*** (0.0004)	No	Yes	0.0070 (0.0065)
Area	No	Yes	-0.0005*** (0.0001)	No	Yes	0.0009* (0.0005)
Age	No	Yes	0.0020*** (0.0001)	No	Yes	-0.0000 (0.0001)
Education	No	Yes	-0.0140*** (0.0001)	No	Yes	-0.0000 (0.0001)
Men	No	Yes	0.0003*** (0.0000)	No	Yes	-0.0000 (0.0000)
Married	No	Yes	0.0001*** (0.0000)	No	Yes	0.0000 (0.0000)
Observations	742,582	742,513	742,513	4,903	4,903	4,903

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A4. Log hourly earnings and job referrals above 5% of the minimum wage for Colombia and Mexico

Variables	Colombia			Mexico		
	(1) Base lwageh	(2) Full lwageh	(3) Explained lwageh	(4) Base lwageh	(5) Full lwageh	(6) Explained lwageh
Job referral	-0.1748*** (0.0025)	-0.0270*** (0.0021)	-0.1478*** (0.0010)	-0.0220*** (0.0017)	0.0323*** (0.0014)	-0.0542*** (0.0010)
Time	No	Yes	-0.0090*** (0.0004)	No	Yes	0.0004 (0.0003)
Area	No	Yes	0.0100*** (0.0002)	No	Yes	-0.0008** (0.0003)
Age	No	Yes	0.0044*** (0.0003)	No	Yes	0.0008** (0.0004)
Education	No	Yes	-0.1539*** (0.0008)	No	Yes	-0.0556*** (0.0008)
Men	No	Yes	0.0009*** (0.0001)	No	Yes	0.0009*** (0.0001)
Married	No	Yes	-0.0001*** (0.0000)	No	Yes	0.0002* (0.0001)
Observations	555,365	555,347	555,347	483,745	483,745	483,745

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1