Online Vacancies and its Role in Labor Market Performance

By: Leonardo Fabio Morales
Carlos Ospino
Nicole Amaral

Borradores de ECONOMÍA

No. 1174
2021

Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia - Bogotá

Vacantes en línea y su papel en el desempeño del mercado laboral[*]

Leonardo Fabio Morales[†] lmoralzu@banep.gov.co

Carlos Ospino[‡] COSP@IADB.ORG

Nicole Amaral[§] nicolea@IADB.ORG

Resumen

Este documento presenta evidencia de que el aumento de vacantes publicadas a través de internet en Colombia ha incrementado la eficiencia del mercado laboral, esto al facilitar que las empresas encuentren trabajadores para cubrir sus posiciones laborales abiertas. En este estudio estimamos curvas de Beveridge, la relación entre desempleo y vacantes; a través de este desarrollo teórico establecido desde los modelos de búsqueda, se concluye que las políticas que aumentan la publicación de vacantes en línea mejoran la eficiencia del mercado. Implementamos un diseño de diferencias en diferencias para aprovechar una regulación, que exige que todos los proveedores de vacantes en línea autorizados reporten cualquier vacante en línea al Servicio Público de Empleo en Colombia. Encontramos que los sub-segmentos del mercado laboral con una fracción significativa de sus vacantes publicadas a través de internet presentaban en promedio una tasa de vacantes casi un 15% menor, para una tasa de desempleo determinada. En el contexto de los modelos de búsqueda, lo anterior implica que en los sub-segmentos afectados por la política, la curva de Beveridge se desplazó hacia adentro. Lo anterior implica una mejora en la eficiencia, dado que para una tasa de desempleo fija, las vacantes se llenaron con más facilidad. Nuestros hallazgos respaldan las políticas de búsqueda activa para reducir las barreras de información, las cuales reducen las probabilidades de que las empresas y los trabajadores se encuentren en el mercado laboral.

JEL codes: J23, J63, J60.

Keywords: Vacantes online, Demanda laboral, Curva de Beveridge.

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[*] We would like to thank Carmen Pagés for her support with this project and her contributions to an earlier version of this document. We thank Estefany Hernandez and Sun Yin Huang for excellent research assistance.

[†] *Banco de la República*, Medellín, Colombia.

[‡] Inter-American Development Bank, Washington DC, USA.

[§] Inter-American Development Bank, Washington DC, USA.

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Leonardo Fabio Morales — lmoralzu@banep.gov.co

Carlos Ospino — COSP@IADB.ORG

Nicole Amaral — nicolea@IADB.ORG

Abstract

This paper assesses whether the expansion of online job vacancies leads to a more efficient labor market. We provide compelling evidence that the increase in online job vacancy penetration in Colombia has had an enhancing effect on the labor market's efficiency by making it easier for firms to find workers to fill their job openings. An estimation of the Beveridge Curve (unemployment to vacancies relationship), a well-established theoretical development from search models, concludes that policies that increase online vacancy posting enhance efficiency. We implement a differences in differences design to take advantage of a regulation, which mandates that all authorized online vacancy providers report any online vacancy to the Public Employment Service in Colombia. We find that sub-segments of the labor market with a relevant fraction of their vacancies posted online, presented on average nearly 15% lower vacancy rate for a given unemployment rate. Therefore, for these sub-segments, the Beveridge curve shifted inwards due to efficiency enhancements. These findings support active search policies to reduce information barriers, which reduce the odds of firms and workers finding one other in the labor market. Policies as those implemented by the Public Employment Service in Colombia seem to be beneficial.

JEL codes: J23, J63, J60.

Keywords: Online vacancies, Labor demand, Beveridge Curve.

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1. Introduction

The number of studies that use data from online job portals to analyze labor market demand has increased recently. These data and other Internet-generated data sources provide valuable sources of information that complement traditional sources due to their granularity, reduced costs, and timeliness (Glaesser et al., 2017). Data from online job portals have been used to shed light on various issues ranging from the returns to cognitive and social skills (Deming and Kahn, 2018) to the development of skills taxonomies (Djumalieva and Sleeman, 2018). However, fewer studies have focused on the analysis of online job vacancies and job searching behavior. For instance, Marinescu and Wolthoff (forthcoming) assess the effect of employers' search strategies. They use data from a large job board containing about one-third of all online vacancies in the United States to evaluate how firms advertise their positions and the number of applicants attracted by these postings.

While Internet-generated data provide valuable new information not often found in other data sources, it comes at the cost of uncertain coverage and representativeness. This critical issue is seldom addressed explicitly **(**Kureková, Bevlavý, and Thum-Thysen, 2015). While the share of vacancies posted online is increasing rapidly, its coverage is still low for some markets, locations, and occupations. Additionally, the underlying population of vacancies is difficult to measure because many firms recruit for new positions through private networks or among their employees; therefore, they do not post online vacancies for those jobs.

Nevertheless, coverage of online job boards has increased markedly in the last decade and is likely to continue. For example, David Autor (2000) reported that about 10% of workers searched for jobs online, while Kuhn and Mansour (2014) found that by 2010, 76% of the unemployed population searched for jobs through online job boards. Despite the rapid emergence of online job portals, very few studies analyze whether such portals (as a form of digitalization of the job search process and a type of employer-job seeking) increase job matching efficiency and make the labor market more efficient.

The Internet's effects on reducing frictions in different markets have been studied in the literature for other cases such as insurance or real state (Brown and Goolsbee, 2002; Kroft and Pope, 2014). Specifically, regarding the labor market, the use of the Internet to advertise job openings is a form of intermediation that changes how job seekers search for jobs and employers fill their vacancies. This kind of technological shock presents an exciting opportunity to study the effect of intermediation on labor market efficiency. To the best of our knowledge, apart from this paper, there are just two studies on the matter. Counterintuitively, Kuhn, and Skuterud (2004) show that unemployed workers who look for work online have longer unemployment durations. Kuhn and Mansour (2014), using the same data for a subsequent period, found that workers who searched for jobs online were reemployed 25% faster than those who used other strategies. The authors hypothesize that this reversal is due to improvements in technology over this period.

From a broader perspective, our study is related to the literature on search channels, but some of the studies on this topic ignore online channels (Holzer, 1988; Blau and Robins, 1990; Thomsen and Wittich, 2010). Most of the literature on search channels is not based on an economic framework suited to model efficiency. Only one study tries to capture the effects of online intermediation on economic aggregates (equilibrium effects). In this study, the authors examined the expansion of the electronic board known as “Craigslist.” They found that online search had reduced housing vacancy rates but had not significantly affected the unemployment rate (Kroft and Pope, 2014). Finally, our study is related to the literature assessing public employment agencies (Osberg, 1993; Addison and Portugal, 2002). The findings on this matter have not reached a consensus. There are still gaps in the literature to be filled, especially when it comes to using Internet technologies by Public Employment Agencies.

Our empirical evidence is based on the Beveridge Curve estimation, a well-developed theoretical tool to analyze labor market efficiency in the search, and matching literature. The Beveridge Curve is an equilibrium relationship between unemployment and vacancies, for a given separation rate. To the best of our knowledge, no other study has answered whether the penetration of technologies to post job vacancies online shifts the Beverage Curve inwards, thus implying a more efficient labor market. For this purpose, we used a combination of administrative records in Colombia, which allowed us to estimate both the total number of vacancies and the number of vacancies posted online at a very granular level. We offer compelling evidence that the penetration of online job posting increases labor market efficiency.

To assess if the expansion of online vacancy posting shifts the Beveridge curve inwards, we use the Colombian government enacted Law 1636 of 2013. This law requires companies to register and report all job vacancies through a network of authorized public and private providers. Starting from 2015, all companies must post their vacancies through one of these authorized providers. All vacancies are aggregated and posted online by a governmental agency created for such a purpose, the "Special Public Employment Service Unit." After the implementation of this public intermediation agency, we find that the segments of the labor market with a relevant fraction of their vacancies posted online presented on average a nearly 15% lower vacancy rate for a given unemployment rate. Therefore, for these sub-segments, the Beveridge curve shifted inwards due to efficiency enhancements.

The rest of the paper goes as follows: in the second section, we describe the peculiarities of the online vacancies reporting system in Colombia, which motivates our empirical test of labor market efficiency. In the third section, we describe the data. The fourth section describes a standard theoretical framework to analyze online vacancy posting and labor market efficiency. In the fifth section, we present the results of our empirical estimations. The sixth section discusses some robustness checks exercises, and finally, in the seventh section, we conclude and offer some policy recommendations.

2. Colombia: Mandatory Vacancy Reporting and the Creation of the National Public Employment Service Unit

Colombia provides an interesting case to study the impact of online job vacancies on labor market efficiency. The country is one of the few in the world that has enacted mandatory reporting of job vacancies to the Public Employment Service Unit. In order to improve the efficiency and transparency of the employment and intermediation process in Colombia, the government enacted Law 1636 of 2013 to regulate the labor market and the employment ecosystem, more specifically, the efficiency and effectiveness of public employment services in Colombia. This policy change resulted from acknowledging the high job search and matching costs for firms and workers in Colombia, which, among other factors, contributed to inefficiency in the labor market and exacerbated unemployment (Arango – Flores 2018).

This law requires companies to register and report all job vacancies through a newly created network of authorized public and private providers. These providers include a range of public and private institutions—including sizeable online job portals, recruiters, municipal public employment services, social services providers (*Cajas de Compensacion*), and university job boards. All companies must post their vacancies through one of these authorized providers, who, in turn, publish them on their web sites, as expected. However, authorized service providers must subsequently report all vacancies to the special Public Employment Service Unit, which is responsible for aggregating and publishing vacancy information on a centralized portal. The portal, in turn, links the information back to the original authorized provider. This scheme implies that the Public Employment Services functions as an aggregator and not a competitor in the online vacancy labor market.

It is important to note that this initiative has faced challenges in its implementation and compliance. Although the law mandating reporting was subscribed in 2013, the special unit was created only until 2015, and vacancy reporting to the Public Employment Services Unit effectively began at that moment. Additionally, the Public Employment Services Unit currently has no real enforcement power. Although many companies have made efforts to comply, many still do not report their vacancies (as noted in later sections of this paper). At the same time, interviews with the Public Employment Services Unit and with a range of authorized providers highlight that quality control of the vacancy information reported and ensuring the removal of duplicated, expired, and/or filled vacancy announcements in the central database is a challenge and an ongoing effort.

Nevertheless, the law has expanded online job portals and increased the number of job vacancies reported online. In this paper, we re-examine the effect of online job posting by assessing whether the expansion in the use of online job portals in Colombia across metropolitan areas has led to more efficient labor markets due to enacting mandatory online vacancy reporting. We seek to contribute to the evidence on the role of Public Employment Services regarding labor market efficiency, mainly through digital transformation strategies such as online job vacancy posting.

3. Online Job Portals and Labor Market Efficiency

How intermediation affects labor market efficiency is an important question, becoming more relevant when a technological shock occurs. Online vacancy posting and online job searching are significant changes in the way job searching is performed. Nevertheless, despite the rapid emergence of online job portals, very little is known whether such portals increase job search efficiency and make the labor market more efficient.

In this section, we discuss how the pervasiveness of online vacancies posting in the Colombian labor market could have substantive implications for the market's performance. In the macro-labor literature, the ideal framework for studying the effects of a new employer-employee matching technology is a Beveridge Curve, the statistical relationship between job vacancies and unemployment. The Beveridge Curve (BC) estimation allows identifying whether online vacancies posting provides efficiency gains in the matching process or not. To ensure our findings' robustness, we estimate the BC using several methodologies; we first motivate the problem using a fixed-effects panel estimation. We exploit Colombia's unique regulation using a difference in differences design. In this method, we take advantage of the policy change induced by the creation of the Public Employment Services Special Unit; this unit is in charge of receiving, analyzing, and re-sharing all the online job vacancies in their information systems.

4. A Gentle Introduction to the Beveridge Curve

The relationship between the vacancy rate and the unemployment rate is known as the Beveridge Curve (BC). The BC's theoretical grounds come from the equilibrium unemployment theory (Mortensen & Pissarides, 1994; Pissarides, 1985). More specifically, this equilibrium relationship is directly derived from a standard matching function, which describes the technology in the generation of employee-employer matches. Matching functions have gained importance in labor market models because they allow modeling frictions with minimal complexity (Petrongolo & Pissarides, 2001). In short, the following equation describes the most basic matching function:

$$M = m(U, V) \qquad (1)$$

where M is the number of employee-job matches, U is the unemployed population, and V is the stock of vacancies. Usually, it is assumed that the matching function is homogenous of degree one; therefore, it is possible to express the number of successful matches as a labor force proportion. The matching function can be expressed in terms of the unemployment rate and vacancy rate.

One of the most important implications of a matching function's definition is the generation of an equilibrium relationship between vacancies and unemployment. Under the assumption of constant returns to scale to the matching function, the probability for an individual to find a job among the stock of open positions at a given moment can be written as the ratio V/U (Anastasopoulos, Borjas, Cook, & Lachanski, 2019). This ratio is the most widely used measure of labor market tightness. An increase in this ratio means more vacancies for a given number of job seekers in a labor market; therefore, the market is tighter. Therefore, there will be more difficulties for employers to fill their vacancies.

In this brief introduction to the concept of BC, we follow Petrongolo and Pissarides (2001). Let us define the level of occupation and the labor force as N and L, respectively. Following the standard definitions, the unemployment rate and the vacancy rate can be expressed as $u = U/L$ and $v = V/N$. If the job separation rate is defined as s, total separations are given by $S =$

sN. In the steady-state, employment growth is null, and separations equal hires. Assuming constant returns to scale in equation (1), we derive the following relation between the separation rate and the vacancy rate:

$$s = \frac{S}{N} = m\left(\frac{U}{L}\frac{L}{N}, \frac{V}{N}\right) = m\left(\frac{u}{1-u}, v\right) \qquad (2)$$

From equation (2), we conclude that for a given separation rate, in steady-state, the relationship between the unemployment rate and the vacancy rate must be negative. This previous description is one of several theoretical justifications for such a negative relationship. In empirical work, several studies corroborate a negative relationship between vacancies and unemployment. The BC behavior depends on the matching function, i.e., the technology governing the formation of new matches in the labor market. Therefore, any enhancement that reduces labor market friction will shift the BC inwards because vacancies are filled more efficiently for a given unemployment rate (see Graph 1).

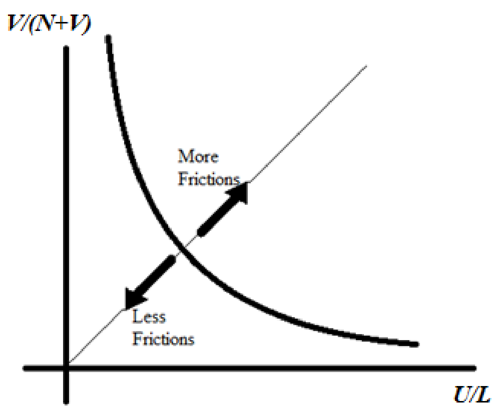
The penetration of new technologies in the search for employees by firms might have implications on reducing search frictions in the labor market. New search technologies might increase the rate at which firms hire new employees, given the vacancies available in a specific market. An expansion in the use of Internet technologies to post vacancies could shift the BC inwards. A BC that is closer to the origin means that open job positions fill faster for a given unemployment rate, and therefore the vacancy rate is lower. Analogously, for a specific vacancy rate, unemployment would be lower. Therefore, the coefficient that accompanies online vacancies' ratio to total vacancies would have a negative sign in a standard BC estimation.

In the literature, there is a long tradition of estimating aggregated BC[6] Many of these studies have called attention to the existence of shifters of the BC not accounted for in its most simplistic form (Petrongolo & Pissarides, 2001). There have been attempts to test the validity of BC shifters in the literature, but there are no studies that examine the implications of online posting on labor market efficiency. One of the earliest studies assessing active labor market policies' effect is Jackman et al. (1990). This paper shows that the BC shifted inwards in countries with higher spending in this type of policy.

[6] as examples of this literature; the reader might consider Howard Wall and Gylfi Zoega (2002), Abraham (1987), Franz (1991); Per Anders Edin and Bertil Holmlund (1991), Giorgio Brunello (1991) for Japan, and Jackman, Pissarides, and Savvas Savouri (1990).

There are several studies concerning a broader spectrum of the relationship between vacancies and labor market shocks. For instance, the one by Davis, Faberman, and Haltinwanger (2013) provides empirical evidence of the critical role of recruitment intensity on accelerating the vacancy filling process. Also, Diamond (2013) analyzes the contribution of out-of-the labor force search on the outward shift in the United States' BC since the great recession in 2008. The central implication for this is that the unemployed and the out-of-the labor force population[7], filling the vacancies. Finally, another supply-side shifter of the BC analyzed in the literature is immigration. In a recent paper, Anastasopoulos, Borjas, Cook, and Lachanski (2019) provide evidence of a BC's inward shift due to an immigration shock in Miami's labor market. For several years after the immigration shock, Miami's labor market became more efficient, thanks to immigration. However, this effect was not permanent, and ten years after the shock, the BC returned to its original position.

Graph 1: Beveridge Curve



5. Data on Total Vacancies and Online Posted Vacancies

This paper uses data on online vacancies provided by the Colombian Public Employment Services (SPE). In its statistical reports, the SPE aggregates online vacancy stocks by metropolitan areas and industries every month. In order to compute a vacancy rate at the level of labor market sub-segment (economic sector in a metropolitan area), we need very granular

[7] should be considered. These later ones are typically students, long-term unemployed or non-working spouses of current workers, and job seekers

information on vacancies stock. For this purpose, we take advantage of a very comprehensive administrative dataset from the Colombian Social Security System.

It is well known in the empirical literature on labor dynamics that measuring vacancies is very difficult; there are very few specialized surveys that allow for direct measurement (Elsby, Michaels, and Ratner, 2015). Further, datasets containing information on vacancies are very uncommon. For instance, in the US, the Job Openings and Labor Turnover Survey (JOLTS) is a remarkable enhancement in the measurement of vacancies. Unfortunately, information of this type is available only for a handful of countries. For the computation of vacancies stocks, we use an employer-employee linked panel generated from administrative records from the "Integrated Record of Contributions to Social Security," PILA. In this panel, we can follow payrolls at the establishment level from 2009 to 2019 at a monthly level, which allows generate hires, separations, and employment size in the standard fashion of the literature on labor flows (see for instance Davis, Haltiwanger, & Schuh, 1996). The PILA contains information for all formal firms, in all economic sectors. This feature is a great advantage because it allows studying the whole format labor market; many empirical studies in labor dynamics deal only with information for a few economic sectors, especially manufacturing (Florez, Morales, Medina and Lobo, 2020).

Even though establishing level information on labor flows is very good, there is no available measure of open positions or vacancies. Therefore, we have to estimate vacancies using the information on labor flows using a methodology proposed by Morales and Lobo (2017), which allows recovering vacancies stocks and flows from employment information, hires, and separations at the level of establishment. Using estimated rather than observed vacancies could cause some measurement error issues since we could add noise in the measurement of the vacancy rate; nevertheless, this problem would affect mainly our dependent variable, and the statistical noise would be captured by estimation regression error as long as it is random. In the next subsection, we explain the methodology for computing the vacancies.

5.1 Methodology for Estimating Vacancies: The Stock of Vacancies as a Function of Hires and Separations

In order to have a magnitude of the universe of all vacancies in the Colombian labor market, we use the methodology proposed by Morales and Lobo (2017); the methodology allows estimating vacancy stock from establishment-level data on employment and worker flows. The procedure is based on estimating a firm's hiring function; this hiring function (see equation 1) represents an accounting identity that explains hiring exclusively as a two-component function: replacement vacancies and expansion vacancies.

$$h_{j,t} = \sum_{\tau=0}^{L} \theta_{\tau} s_{j,t-\tau} + \sum_{\tau=0}^{R} \phi_{\tau} \vartheta_{j,t-\tau} + \epsilon_t \quad (1)$$

where s_t stands for the total number of separations in a firm at period t; the first summation of the equation represents vacancies generated by the separation of workers, which firms decide to replace. In addition, ϑ_t represents the number of new job positions opened by the firm at period t; the second summation in equation (1) represents the total vacancies of new open job positions. Total hires, $h_{j,t}$ is given by a polynomial lag of $s_{j,t}$, and $\vartheta_{j,t}$ because either replacement or expansion vacancies may not be filled contemporaneously given labor market frictions.

The challenge with estimating equation (1) is that expansion vacancies ϑ_t are not observed directly in the data; nevertheless, we observe hiring and separations directly from PILA. Using control function methods, one can get an estimate of ϑ_t by using the following algorithm:

1. Estimate $h_{jt} = \sum_{\tau=0}^{L} \theta_{\tau} s_{jt-\tau} + \alpha_{jt} + u_{jt}$. The estimated fixed effect $\hat{\alpha}_{jt}$ is an estimate of the unobserved component $\sum_{\tau=0}^{R} \phi_{\tau} \vartheta_{t-\tau}$ in equation (1); Let us assume that $E[\vartheta_t]$ is constant during R periods; therefore, $\hat{\alpha}_{jt}$ is an estimate for $E[\vartheta_t] = \boldsymbol{\vartheta_t}$.

2. Assuming that the flow of the expansion vacancies follows a Poisson process, $\vartheta_{jt} \sim poisson(\boldsymbol{\vartheta_t})$, generate a draw of ϑ_{jt} from a Poisson distribution $\tilde{\vartheta}_{jt} \sim poisson(\widehat{\alpha_t})$. Then estimate the following equation that represents the identity that in every period, the change in employment, Δe_{jt}, should be equal to the difference between hires and separations:

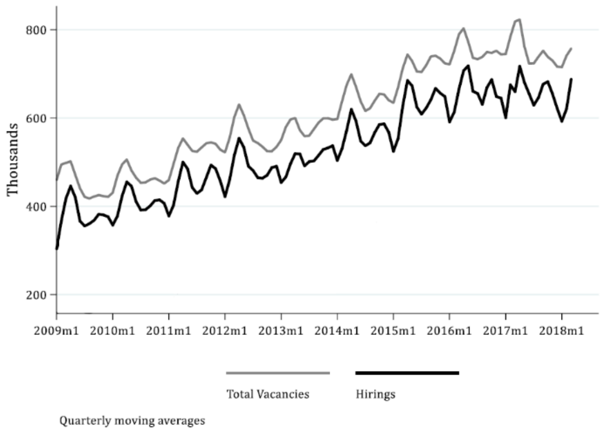
$$\Delta e_{jt} = (\theta_0 - 1) s_t + \sum_{\tau=1}^{L} \theta_{\tau} s_{jt-\tau} + \sum_{\tau=0}^{R} \phi_{\tau} \tilde{\vartheta}_{jt-\tau} + \epsilon_t$$

3. Repeat steps 1 and 2 for a number I of new draws of $\tilde{\vartheta}_{jt}$, then recover a sample distribution of coefficients $\widehat{\theta}_{\tau}$ and $\hat{\phi}_{\tau}$.

4. Finally, with the sampling average of $\widehat{\theta}_{\tau}$ and $\hat{\phi}_{\tau}$ and $\tilde{\vartheta}_{jt}$, and with the observed s_t compute the stock of vacancies[8].

Using this procedure, we obtain a measure of the stock of vacancies, which behave realistically in the formal Colombian labor market context. In Graph 2, we show the estimate of the total vacancy stock and total hires from PILA for the 23 main metropolitan areas (MA) in Colombia. Graph 2 shows that vacancies evolve similarly to hires. However, since there are frictions in the labor markets, and vacancies cannot be filled instantaneously, vacancies are always higher than the level of hires. In Graph 3, we show the aggregated vacancy rate and the unemployment rate for the main 23 MA areas in Colombia. The relationship between the unemployment rate and vacancy rate is expected: in times of high unemployment, the vacancy rate is low; when unemployment is low, the vacancy rate increases. Applying the methodology explained in this sub-section, we obtain vacancies at the establishment level. We then aggregate the stock of vacancies by sub-segments of economic sectors in a metropolitan area. We compute the vacancy rate at this level of aggregation.

Graph 2: Total stock of vacancies and hires



Notes: Graph 2 shows aggregated hires calculated from PILA, and total vacancy stock computed from hiring, separation, and employment from PILA using methodology presented in section 3.1.

Graph 3: Unemployment Rate and Vacancy Rate

Notes: Graph 3 compares the vacancy rate as the ratio vacancy stock/total jobs and unemployment rate; for the unemployment rate, we use official

[8]. Let us refer to V_t^e and V_t^r as the stock of expansion and replacement vacancies. They are the sum of all vacancies that were generated in previous periods, but they have not been filled completely, the total stock of vacancies is $V_t = V_t^e + V_t^r$

$$V_t^e = (1 - \phi_0 - \phi_1 - \cdots - \phi_{R-1})\, \vartheta_{t-R-1} + (1 - \phi_1 - \cdots - \phi_{r-2})\, \vartheta_{t-R-2} + \cdots + (1 - \phi_0)\, \vartheta_t$$

$$V_t^r = (\pi - \theta_0 - \theta_1 - \cdots - \theta_{L-1}) s_{t-L-1} + (\pi - \theta_0 - \theta_1 - \cdots - \theta_{L-2}) s_{t-L-2} + \cdots + (\pi - \theta_0) s_t$$

reports from the Colombian National Statistics Bureau.

5.2 Additional sources of information

Additionally, we use data from the official Colombian Household Survey (known as GEIH) collected by the National Department of Statistics (DANE). The GEIH is a monthly survey and is representative of the 23 main metropolitan areas across the country and ten industries. The survey includes comprehensive information on the labor market, and it is the source of the official labor market statistics in Colombia (Bonilla et al., 2020). Finally, we use other standard labor flow measures, such as hires and separation rates. The source of this information is the Integrated Record of Contributions to Social Security (PILA by its acronym in Spanish). As mentioned before, the PILA allows us to measure the number of new hires, separations, and employment by industry, metropolitan areas for each month in our sample period.

Table 1 shows the summary statistics of the variables. The average ratio online vacancy to total vacancies for the sub-segments sector-MA from 2015 on was 20,6%. On average, a subsegment of the market post only 1/5 of its vacancies online. The average unemployment rate is 12.4%, and the average vacancy rate is 11.06%. The average number of years of education in each sub-segment is 10.5, and 31% of workers have tertiary education in the average sub-segment. The average separation and hiring rates are 9% and 9.7%, respectively. Finally, most of the employment is concentrated in Services, Trade, Construction, and Manufacturing.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.
Vacancy Rare	30337	11.06	8.31
Unemployment Rate	30339	12.44	3.22
Online Vacancy Share After 2014	12400	20.6	26.9
Employment	30339	26469	80590
Wage	28712	1283180	1073277
Years of education	29636	10.49	2.54
Share of 25+ with college	29636	0.31	0.23
Separation Rates	30106	8.95	7.36
Hiring Rate	30106	9.70	7.91
Employment Agriculture	30339	4701.52	6116.51

Employment Mining	30339	1476.99	3265.85
Employment Manufacturing	30339	75844.38	141524.80
Employment Electricity	30339	2688.85	3912.14
Employment Construction	30339	31671.21	49483.67
Employment Trade	30339	149611.40	239257.90
Employment Transportation	30339	46622.81	75264.30
Employment Finance	30339	10064.03	23493.55
Employment Real Estate	30339	52234.47	115992.20
Employment Services	30339	110869.50	189783.30

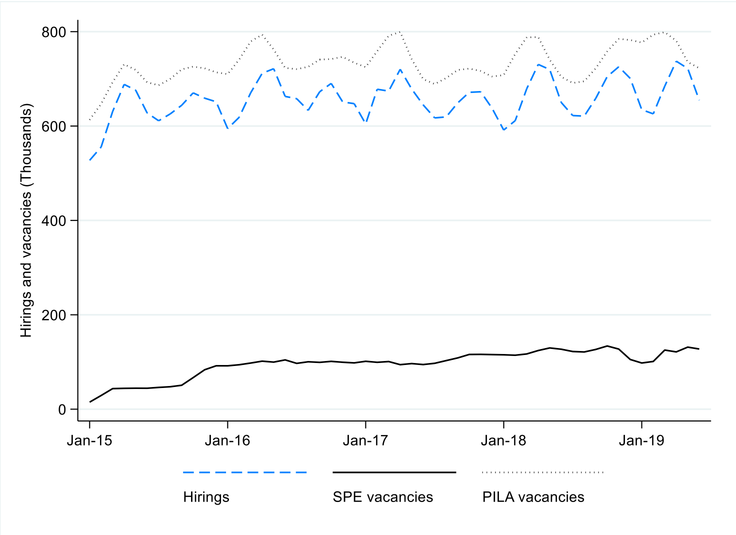
Notes:
Source: Own calculations based on PILA and the Colombian Public Employment Office. The separations (hiring) rate is computed as the total ratio separations (hires) in the labor market subsegment to the moving average of employment of order two. The vacancy rate is computed as the ratio vacancies stock to the labor force. Wage is presented in Colombian pesos. Let us define the level of occupation and the labor force as N and L, respectively. Following the standard definitions, the unemployment rate and the vacancy rate can be expressed as $u = U/L$ and $v = V/N$.

6. Estimation of a Beveridge Curve using Labor Market Level data

This section estimates the Beveridge Curve using the information on total vacancies and the information on the stock of total vacancies posted online. The data about the number of online vacancies come from the Colombian Public Service Employment (SPE) monthly report. The stock of vacancies from the Public Employment Service's statistical reports underestimates total vacancies. This discrepancy is likely due to the PES's limited power of enforcement and sanction over companies that choose not to publish their vacancies through an authorized provider. However, it could also reflect alternative search mechanisms by Colombian firms. Graph 2 shows total hires using social security records from 2009 to 2018. There is a sizeable number of hires in the Colombian labor market (over 600 thousand annually for the period 2009-2018). We expect the stock of vacancies to be higher than total hires, because, in the presence of labor market frictions, vacancies are not filled immediately.

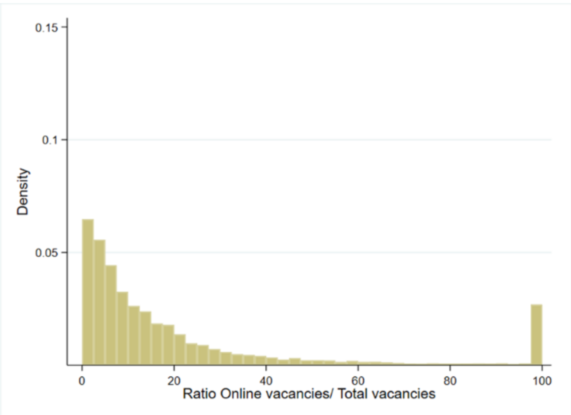
As illustrated in Graph 4, the total stock of online vacancies reported in the SPE for the period 2015-2019 is just a fraction of the estimated stock of vacancies in the formal Colombian labor market. Graphs 5 and 6 show the distribution of the online vacancies share (OVS) aggregated at the metropolitan area and industry level in a metro-area (MA). OVS=$\left(V^{on-line}/V\right)$ is defined as the number of online job vacancies reported by the PES divided by the estimated number of vacancies from social security administrative data. When analyzing the OVS ratio by sector-MA, we found that for some industries within an MA, online vacancy posting is very high. Still, there is a sizeable number for which it is close to zero.

Graph 4: Hiring vs. PILA Vacancies (2016-2019)

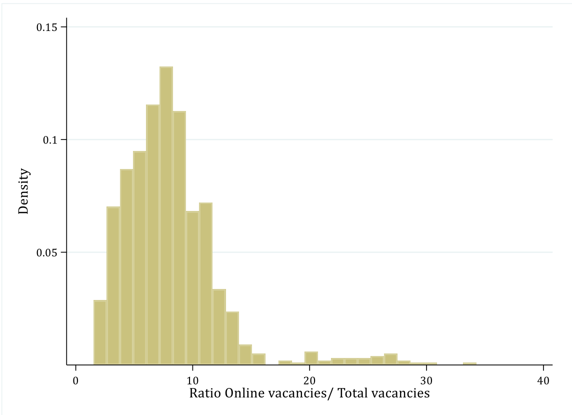


Notes: Graph 3 compares total hires, total vacancy stock, and UASPE vacancies, the later collect the entirety of online posted vacancies.

Graph 5: Distribution of the OVS (Industry-Metropolitan Area)



Graph 6: Distribution of the OVS (Metropolitan Area)



Notes: Graphs 5 and 6 show histograms of the ratio UASPE vacancies/Total stock vacancies; this later variable, computed at the level of sector-MA, and MA, respectively. Source: Calculations by the authors based on data from the Central Bank of Colombia, PILA, and the Colombian Public Employment Office.

A Difference in Difference Estimation of the Market level BC

In 2013, the Colombian government created a management unit for the PES agency, intended to implement active search policies, among other duties. This new agency (henceforth known as UASPE) is in charge of collecting, organizing, and replicating all the information on employers' vacancies on the PES website. In January 2015, the UASPE started publishing vacancies reported by employees in all its information platforms. This information is provided in monthly statistical reports showing the number of online vacancies by metropolitan area and industry. We organize the information every month at the industry level within a MA, allowing us to perform a difference in difference estimation taking advantage of the time variation before and after the UASPE started to collect and report information. This is a robust way to identify the effect of online search technologies' penetration on labor market efficiency.

All industries in the 23 main labor markets in Colombia benefited from implementing the online vacancies posting service by the UASPE. Nevertheless, as we discussed earlier, there is much heterogeneity in the use of online vacancies posting. In general, the number of online-posted vacancies is a smaller sample of the stock for total vacancies, given the number of hires observed in the formal labor market in Colombia (see Graph 3). The total SPE vacancies posted online for the 23 Colombian MAs represent, on average, 13.2% and 15% of the entire monthly stock of vacancies and hiring, respectively.

As shown in Graph 6, for some MA, the SPE-vacancies could represent up to 40% of total vacancies stock, but in some cases, they represent a tiny fraction of total vacancies. When it comes to industries within a MA (See Graph 5), in average, 20.6% of the total stock of vacancies were posted online. In this latter case, some industries are fully represented; nevertheless, for a sizeable set of industries, the online posting technology's penetration is close to zero. For our baseline estimation, using the continuous OVS variable, we define a treatment variable for the SPE services. We define as treated units those for which the OVS is at least 30% on average over January 2019 to March 2019. We chose this threshold because this is equivalent to define treated sub-segments are the ones in which the OVS is greater than the average after 2015 for the whole sample (20.6%). In other words, a labor market sub-segment is considered treated if its OVS is greater than the average, and it is considered as control if the OVS is less than the average. In any case, our treatment definition does not change in time. We acknowledge that this definition of treatment for the baseline estimation is arbitrary; nevertheless, we show results for a broad family of thresholds, and our main results and conclusion hold. Furthermore, in the robustness checks we comment later, our main conclusion does not change when we use alternative treatment definitions. Our estimation of a Beveridge Curve in the context of a standard difference in difference framework can be represented as:

$$Ln(v_{s,j,t}) = \beta_0 + \beta_1 \ln(u_{jt-3}) + \beta_2 post + \beta_3 treated * post + x'_{j,t}\beta_3 + \gamma_{sj} + \varepsilon_{i,j} \quad (2)$$

where $v_{j,s,t}$ and $u_{j,t-3}$ stand for the vacancy rate and the unemployment rate, respectively. We lagged the unemployment rate a quarter to minimize any simultaneity bias. In addition, γ_{sj} are unit fixed effects (industry-MA). In a recent paper, Bilinski and Hatfield (2019) show that allowing for more complex trends is crucial in differences in differences designs. These trends should differ between treatment and control groups. Therefore, in all specifications, we control for a polynomial trend of order 3, which in turn is interacted with the treatment variable to allow differentiated time trends for treated and controls units. In some specifications, we allow the unemployment rate to have a differentiated effect in each industry by interacting dummy variables $1\{industry = s\}$, representing industry dummies with the unemployment rate. Finally, we estimate regressions without control variables. Then we add the separations rate first, which is crucial for the theoretical derivation of the Beveridge curve (see equation 1). For a full specification, we include the share of older than 25 workers with college, average workers years of education, and the average wage log.

Estimation results of equation (2) are presented in Table 2. Regressions in Columns 1, 2, and 3 include the unemployment rate (UR) without any interaction. Columns 4, 5, and 6 include the unemployment rate (UR) interacted with industry dummy variables. Regressions in columns 1 and 4 do not include controls, regressions in columns 2 and 5 include the separation rate as a control, and finally, regressions 3 and 6 include additional controls. The treatment effect, which is given by $\hat{\beta}_3$, is negative and statistically significant in all specifications; therefore, the treated labor markets (those with an OVS greater than average) had a significant inward shift in the Beveridge curve. The magnitude of this effect is sizeable; in the specification in which we control for the separations rate, holding everything else constant, we identify a reduction in vacancy rate treated segments of the labor market around 14%, which is equivalent to a reduction of 1.4 percentage points (pp). The policy of active searching by the UASPE had a significant effect in reducing frictions in the labor markets in which it was more intensively adopted. In sub-markets more affected by the policy, vacancies are filled more efficiently, which implies a reduction in the vacancy rate for a given unemployment rate.

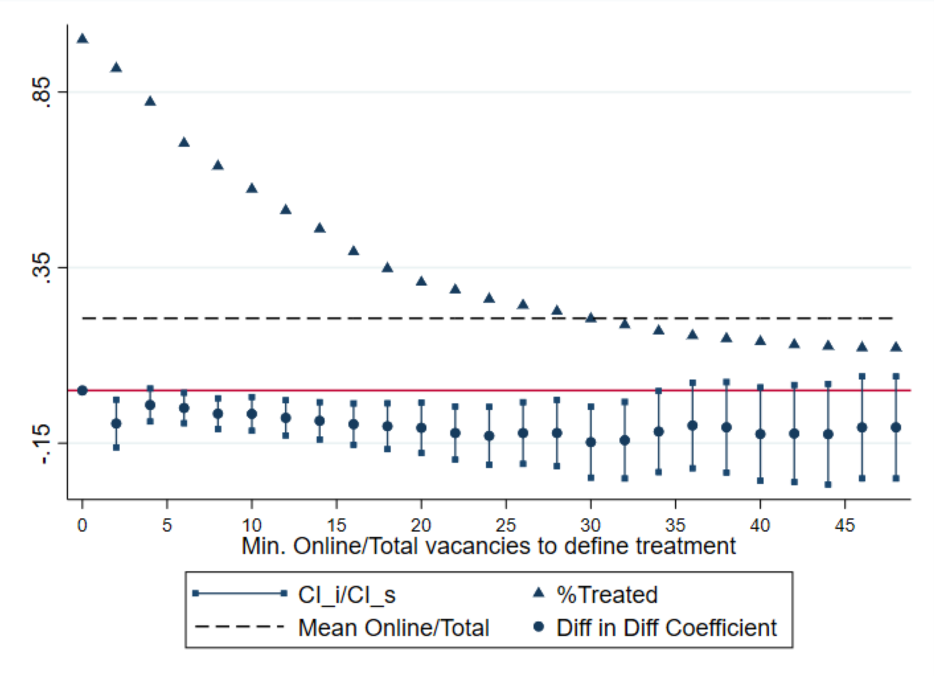
Table 2: Diff in Diff Estimation BC at the Sector-MA Level

VARIABLES	(1) Ln(VR)	(2) Ln(VR)	(3) Ln(VR)	(4) Ln(VR)	(5) Ln(VR)	(6) Ln(VR)
Post	0.0986***	0.0052	-0.0043	0.0988***	0.0051	-0.0045
	(0.0197)	(0.0114)	(0.0102)	(0.0198)	(0.0116)	(0.0102)
Treatment*Post	-0.2353***	-0.1417***	-0.1490***	-0.2363***	-0.1407***	-0.1471***
	(0.0732)	(0.0543)	(0.0525)	(0.0725)	(0.0539)	(0.0516)
2.sector*UR				-0.0142	-0.0182**	-0.0205***
				(0.0120)	(0.0081)	(0.0075)
3.sector*UR				-0.0341***	-0.0198***	-0.0195***
				(0.0059)	(0.0053)	(0.0051)
4.sector*UR				-0.0004	0.0015	-0.0002
				(0.0099)	(0.0089)	(0.0087)
5.sector*UR				-0.0080	0.0024	0.0033
				(0.0053)	(0.0031)	(0.0032)
6.sector*UR				-0.0203***	-0.0099***	-0.0091***
				(0.0049)	(0.0032)	(0.0031)
7.sector*UR				-0.0011	0.0006	0.0005
				(0.0059)	(0.0040)	(0.0039)
8.sector*UR				0.0072	0.0010	-0.0006
				(0.0100)	(0.0066)	(0.0063)
9.sector*UR				-0.0023	0.0002	0.0002
				(0.0046)	(0.0032)	(0.0031)
10.sector*UR				-0.0089**	-0.0047*	-0.0043*
				(0.0039)	(0.0025)	(0.0023)
UR	-0.0094***	-0.0055***	-0.0053***			
	(0.0027)	(0.0018)	(0.0017)			
Separation Rate		0.0439***	0.0473***		0.0438***	0.0473***
		(0.0022)	(0.0019)		(0.0022)	(0.0019)
Constant	2.1092***	1.6210***	1.5742***	2.1097***	1.6218***	1.5733***
	(0.2206)	(0.1511)	(0.1731)	(0.2221)	(0.1517)	(0.1720)
Observations	26,182	26,182	24,759	26,182	26,182	24,759
R-squared	0.0136	0.4778	0.4886	0.0184	0.4802	0.4910
FE	Yes	Yes	Yes	Yes	Yes	Yes
T*Trend3	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes

Notes: * significant at 10%; ** significant at 5.0%; *** significant at 1.0%. The dependent variable is the log of the vacancy rate (see equation 2). The observation unit is the sub-segment industry-MA. In all regressions, we control for unit fixed effects and polynomial-time trends (order 3). Regressions allow for different trends for treated and control units. Regressions in Columns 1, 2, and 3 include the unemployment rate (UR) without any interaction. Columns 4, 5, and 6, include the unemployment rate (UR), interacted with industry dummy variables. Regressions in columns 1 and 4 do not include any controls; regressions in columns 2 and 5 include separation rate as a control. Finally, regressions 3 and 6 include additional controls at the sub-market level: log of the average wage, the share of older than 25 workers with college, average workers years of education. Standard errors in parenthesis are clustered at the sector-AM level.

Since our definition of treatment is arbitrary, we run a family of estimations of equation (2) changing the threshold for treatment definition. For this exercise, we set a threshold $K \epsilon [0,1]$, and define treatment variables as $treatment_k = 1\{\overline{OVS}_{j,s} > K\}$. In other words, a sub-segment is treated if its average OVS is greater than K percentage. We use the most comprehensive specification in these regressions, but results are similar in regressions without additional controls. Results are presented in Graph 7, each circle represents the difference in difference coefficient β_3 of a regression with different thresholds K. For instance, using a K=0.3, the treatment is equal to one for sub-segments where the OVS is at least 30%. As the reader might notice, this is the same definition we use in the baseline estimation. In this case, the coefficient is 0.14. The triangles represent the percentage of the units in the whole sample classified as treated; when the threshold is low, the share of treated units is high. For thresholds higher than 45%, the percentage of treated falls below 10%. The difference in difference coefficient is negative for all thresholds between 2% and 50%; in addition, it is significant for almost all thresholds between 2% and 35%. For higher thresholds, the diff in diff coefficient is more imprecisely estimated, therefore, it is no longer significant because the standard errors become larger, which is natural given that the percentage of units treated reduces.

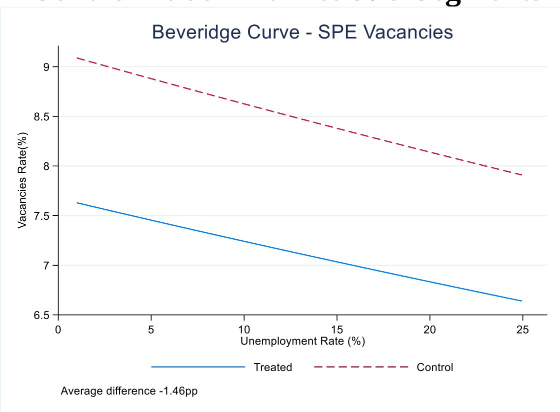
Graph 7: Sensibility of the diff in diff coefficient to treatment definition



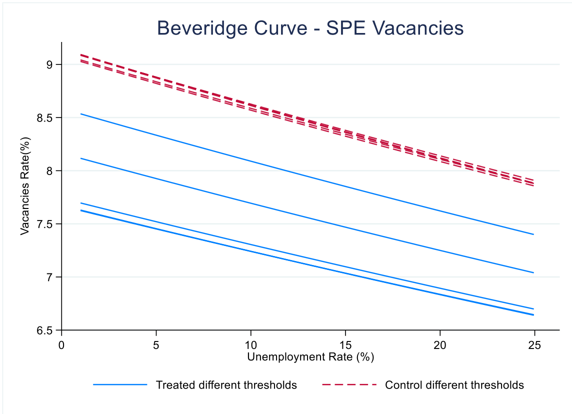
Notes: In this graph, each interaction coefficient β_2 in equation (2) is represented. The interaction terms are the multiplication of the treatment dummy with the post dummy. Confidence intervals are constructed at a 95% confidence level. In the regression, we control by time-fixed effects and by differentiated (cubic) time trends.

To reach a better understanding of the magnitude of the difference in difference coefficient in Graph 8 we simulate the BC's average movements for the treated and control labor market segments. The BC for the treated sub-segments shifted inwards: for every value of the unemployment rate, the treated sub-segments' vacancy rate would be nearly 1.4 pp smaller on average. As mentioned before, the magnitude id the inward shift would depend upon the definition of the treatment; nevertheless, as presented in Graph 9, for a broad spectrum of treatment definition, we identify inward shifts. This last point is illustrated in in Graph 8, in which different BC are simulated for a set of different thresholds K=10, 20, 30, 40, 50. The magnitude of the BC's movements is between -0.6pp and -1.5pp in average.

Graph 8: Simulated BC for Treated and Control Labor Market Sub-Segments



Graph 9: Simulated BC for Treated and Controls for different thresholds



Notes: Graph 8 is based on the estimation of equation (2) (specification [4] in table 2). The solid line is the prediction of the vacancy rate for treated market sub-segments, and the dotted line is the prediction of the vacancy rate for control market sub-segments. The average difference is of 1.46 percentage points (pp). Graph 9, present the Bevereridge curve for treated and control units, for a set of different thresholds K=10, 20, 30, 40, 50. The magnitude of the BC's movements is between -0.6pp and -1.5pp in average.

In section 6, we perform a series of alternative robustness checks to validate our main conclusion that higher penetration of online job vacancies enhances overall labor market efficiency. Our results are robust to further changes in the definition of treatment. A plausible causal interpretation of the SPE's active search policies would require that, before the implementation of such policies, the vacancy rates show parallel trends for the treated and non-treated sub-segments of the labor market. This is an assumption, which we can test in the context of event study research designs.

Event Studies

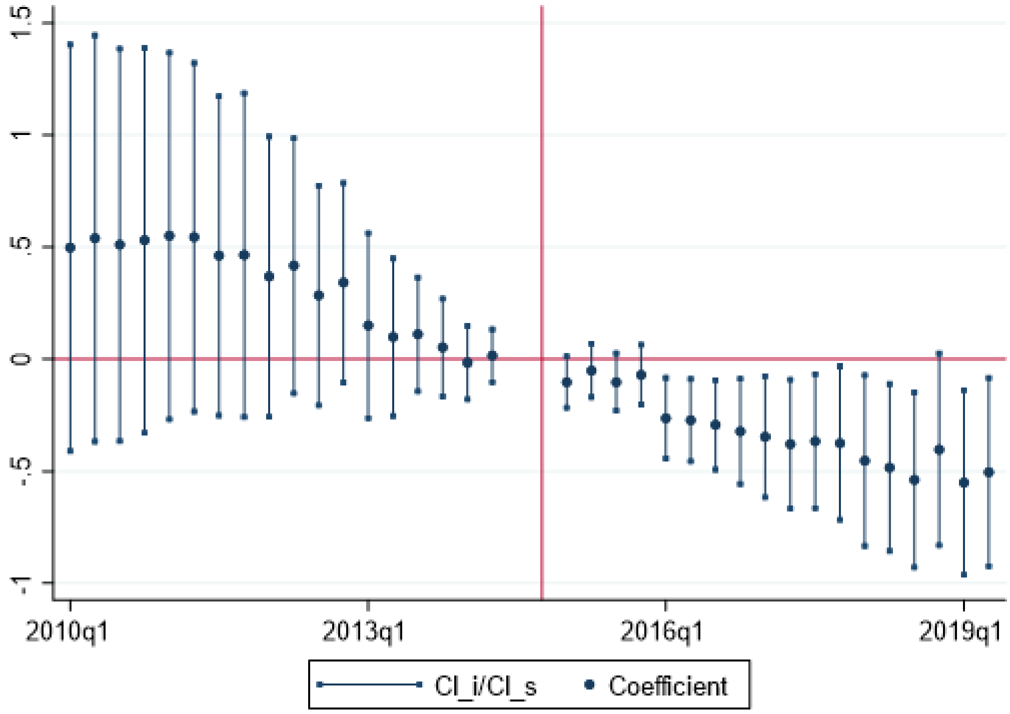
The validity of the previous results depends on the standard assumptions of difference in difference causal estimation. We test the existence of parallel trends in the context of an event study. The estimation is analogous to equation (2). Instead of introducing a single interaction term between the post-treatment period and the treatment indicator, we introduce several interactions of the treatment variable with time dummy variables. As is common in this type of regressions, we take the year before implementing the policy as a reference category, in our case, 2014. The estimated equation can be represented as:

$$Ln\left(v_{s,j,t}\right) = \beta_0 + \beta_1 \ln\left(u_{jt-3}\right) + \beta_{2,q} 1\{t = q\} + \sum_q \beta_3 treated * 1\{t = q\} + x'_{j,t}\beta_3 + \gamma_{sj} + \varepsilon_{i,j} \quad (3)$$

The regression is similar to the previous equation (3), but instead of a unique interaction of treatment and post-treatment dummies, we include several year-treatment interactions. Furthermore, following Bilinski and Hatfield (2019), we include (cubic) trend polynomials, and we interacted with these polynomials with the treatment dummy. Results of the event study are summarized in Graph 4, and the results of the regression are presented in Appendix F. During the four years before the implementation of the UASPE, there are no statistically significant differences between treated and control labor markets. We obtain this parallel trend evidence even after controlling for polynomial-time trends differentiated for treatment and control groups.

We interpret this evidence as consistent with a causal interpretation of the difference in difference estimation. In the year that the information system of the UASPE was implemented (2015) there was no significant effect. This previous finding is not an expected result because the information system had been just implemented, and it needed time to gain recognition and users. Graph 3 shows how the level of vacancies jumps at the end of 2015. For the years after the implementation, we identify negative and significant effects during the period 2016 to 2019. Therefore, during these years, the impact of efficiency enhancement was taking place. This estimation, together with the difference in difference regression results discussed before, constitutes evidence that an increase in online vacancies' share shifted the Beveridge curve inwards, improving labor market efficiency.

Graph 10: Event Study Results (year-quarter)



Notes: In this graph, each of the interaction coefficients $\beta_{2,\tau}$ in equation (3) is represented. The interaction terms are the multiplication of the treatment dummy with year-fixed effects. Confidence intervals are constructed at a 95% confidence level. In the regression, we control by time-fixed effects and by differentiated (cubic) time trends. Regression results are presented in Appendix G.

7. Robustness Checks

This section provides evidence that our results are robust to further changes in specification and treatment definitions. We perform a series of alternative robustness checks to validate our main conclusion that higher penetration of online job vacancies enhances overall labor market efficiency. We first check that the assumption of parallel trends holds for any of the treatment definitions in Graph 7; as the reader might remember, we define treatment variables using a wide range of thresholds in this graph. In Appendix A, we present the result of several event study designs in which we define treatment using different thresholds. The parallel trend hypothesis is not rejected in any of the regressions.

In our baseline regressions, we use the average online vacancies ratio to define treatment ($treatment_k = 1\{\overline{OVS}_{j,s} > K\}$), and our baseline specification is with $K = 30\%$, which is equivalent to define treatment if $\overline{OVS}$ is higher than the global mean. In a series of robustness checks, we change the construction of the treatment variable; we use the maximum of the online vacancies ratio for defining the treated unit, instead of using the mean. Therefore, we define the unit as treated if it ever reaches a level of online vacancies ratio. As part of our sensitivity analysis, we run a series of differences in difference regression using treatment defined in this new way ($treatment_k = 1\{\max(OVS_{j,s}) > K\}$). The difference in difference coefficients are presented in Appendix B1; each circle represents the difference in difference coefficient β_3 of regressions with different thresholds *K*. The triangles represent the percentage of the units in the whole sample classified as treated under each specific definition. For a wide range of thresholds under this new definition, the difference in difference coefficient is negative and statistically significant; specifically, coefficients are significant in a segment of thresholds from *K*=30% to *K*=75%, and the magnitudes converge to similar values we report in the baseline estimation (0.14). In Graph B2, we represent the inward shift of BC using different thresholds for the treatment definitions. Finally, in Graph B3, we show that the hypothesis of parallel trends before implementing the policy is not rejected at any of the thresholds used for this new treatment definition.

A possible caveat of the definition of treatment is that it is based on the ratio online vacancies to total vacancies. We represent the online vacancies ratio as the ratio of online vacancies to total vacancies in all baseline estimations. This last variable is computed by using hires and separation as primary inputs. This calculation could add measurement error to our treatment definition, which can be problematic in an independent variable. In an additional set of robustness exercises, we computed the ratio as online vacancies to total hires. Total hires are directly observed from the social security records; therefore, we define treatment as $treatment_k = 1\{\overline{online\ vacancies/hires}_{j,s} > K\}$. In other words, a sub-segment is treated if its ratio online vacancies to total hires are greater than *K* percentage. In Appendix C, we show the results of the differences in differences design and the event studies for this robustness check. The differences in differences coefficients are presented in Appendix C1 for different thresholds *K*. The difference in difference coefficient is negative and statistically significant for a broad segment of thresholds, and the magnitudes converge to similar values we report in the baseline estimation (0.14). In Graph C2, we represent the inward shift of BC using different thresholds for the treatment definitions. Finally, in Graph C3, we show that the hypothesis of parallel trends before implementing the policy is not rejected for most of the thresholds used for this new treatment definition. Nevertheless, in cases in which there are no parallel trends, the difference in the opposite sign to the effect we find of the policy on the vacancy rate.

8. Conclusions

Despite the rapid emergence of online job portals and the increasing number of studies using these data, very few studies analyze whether such portals increase labor market efficiency or not. To the best of our knowledge, the only paper that has reported a beneficial effect is that by Kuhn and Mansour (2014), who found that workers who searched for jobs online were reemployed 25% faster than those who used other search strategies. This paper uses the standard theoretical framework in the macro-labor literature to study search frictions in the matching process, the Beveridge Curve. A well-known result from equilibrium unemployment models is that any shock that reduces labor market frictions will shift the BC inwards; therefore, vacancies are filled more efficiently for a given unemployment rate.

We provide evidence that the increase in online vacancy penetration has a positive effect on the labor market's efficiency by making it easier for firms to find workers that fill their job openings. An estimation of the Beveridge Curve at the level of industry-MA sub-segments of the labor market concludes that the Online Vacancies Ratio, the proportion of all vacancies posted online, is a negative shifter of the Beveridge Curve. After implementing the active search policies from the Public Employment Service in Colombia, we find that sub-segments of the labor market with a relevant fraction of their vacancies posted online presented on average nearly 15% lower vacancy rate for a given unemployment rate. In the context of equilibrium search models, in sub-segments affected by the policy, the Beveridge curve shifted inwards as a result of efficiency enhancements. This result holds in our differences in differences regressions, event study designs, and a series of robustness checks.

Our findings support active search policies aimed at reducing informational barriers that increase matching frictions. Policies as those implemented by the PES in Colombia, in which there is a mandatory online vacancy reposting system, seem to be beneficial. The penetration of online posting is still low. The representativeness of online vacancies in the total stock of vacancies is only 20% in an average industry, meaning there is still a significant margin for efficiency gains.

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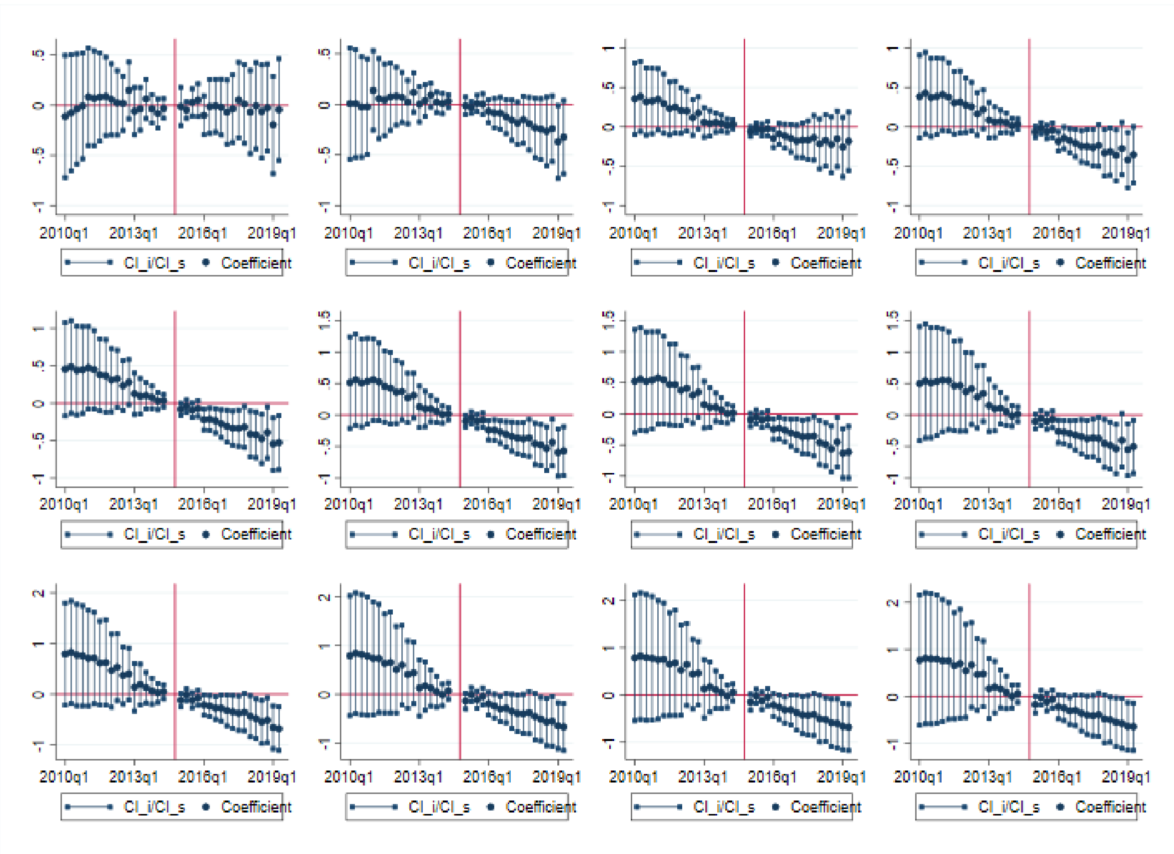
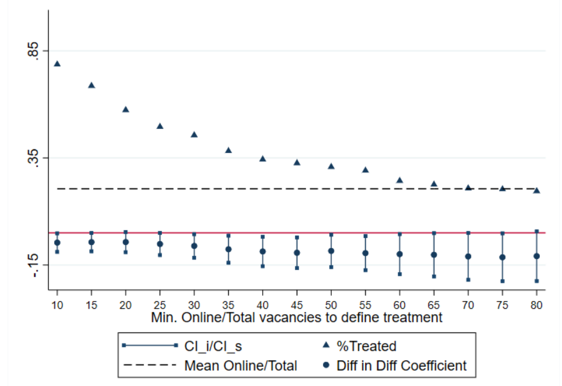
Appendix A: Even Study Design for different Thresholds:



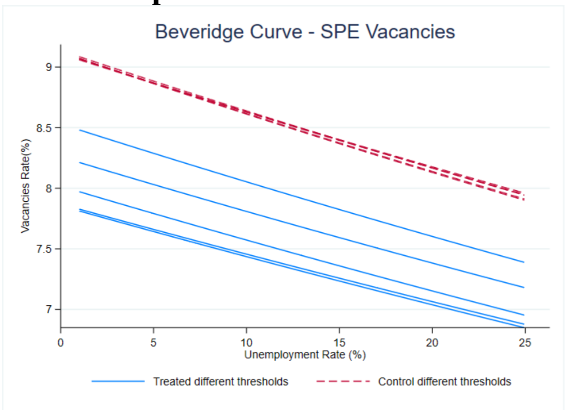
Notes: In the sub-panel of this graph, each of the interaction coefficients $\beta_{2,\tau}$ in equation (3) is represented. The interaction terms are the multiplication of treatment dummy with year-fixed effects. Confidence intervals are constructed at a 95% confidence level. In the regression, we control by time-fixed effects and by differentiated (cubic) time trends. From left to right and top to bottom, the values of each panel's thresholds are the following: K=2, 4,12, 16, 20, 24, 28, 30, 34,40,44, 48.

Appendix B: Ever Treated Difference in Difference and Event Study Design

Graph B1: Sensitivity Analysis

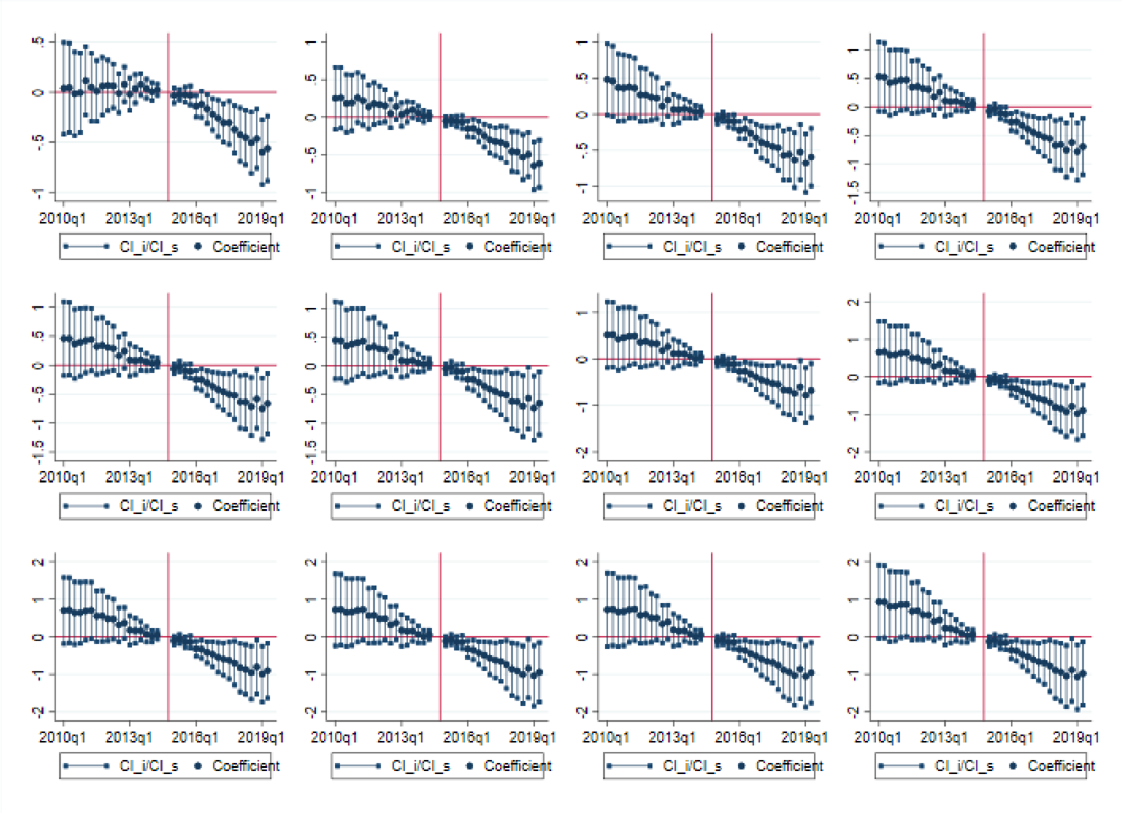


Graph B2: BC Inward Shifts



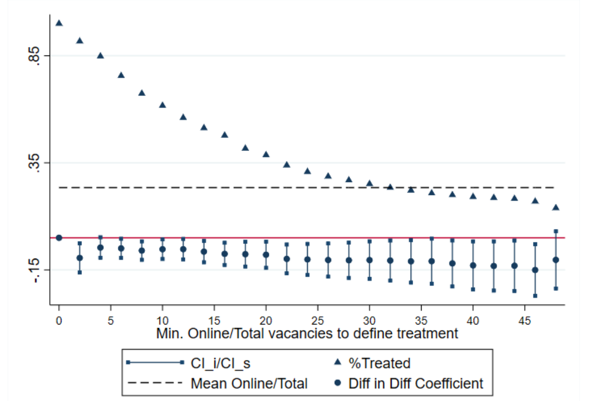
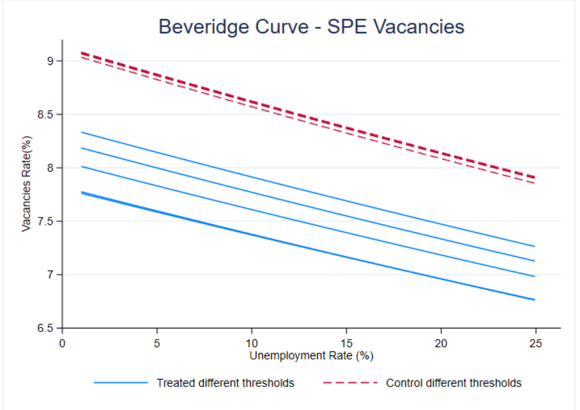
Notes:
In this graph, each one of the interaction coefficients β_2 in equation (2) is represented. The interaction terms are the multiplication of the treatment dummy with the post dummy. Confidence intervals are constructed at a 95% confidence level. In the regression, we control by time-fixed effects, and by differentiated (cubic) time trends.
Graph B2 is based on the estimation of equation (2) (specification [4] in table 2). The solid line is the prediction of the vacancy rate for treated market sub-segments, and the dotted line is the prediction of the vacancy rate for control market sub-segments. Graph B2 presents the Beveridge curve for different thresholds K=10, 20, 30, 40, 50.

Graph B3: Ever Treated Even Study Design Results



Notes: In the sub-panel of this graph, each of the interaction coefficients $\beta_{2,\tau}$ in equation (3) is represented. The interaction terms are the multiplication of treatment dummy with year-fixed effects. Confidence intervals are constructed at a 95% confidence level. In the regression, we control by time-fixed effects and by differentiated (cubic) time trends. From left to right and top to bottom, the values of each panel's thresholds are the following: K=2, 4,12, 16, 20, 24, 28, 30, 34,40,44, 48.

Appendix C: Ever Treated Difference in Difference and Event Study Design

Graph C1: Sensitivity Analysis	Graph C2: BC Inward Shifts
	

Notes:
In this graph, each one of the interaction coefficients β_2 in equation (2) is represented. The interaction terms are the multiplication of the treatment dummy with the post dummy. Confidence intervals are constructed at a 95% confidence level. In the regression, we control by time-fixed effects and by differentiated (cubic) time trends.
Graph B2 is based on the estimation of equation (2) (specification [4] in table 2). The solid line is the prediction of the vacancy rate for treated market sub-segments, and the dotted line is the prediction of the vacancy rate for control market sub-segments. Graph B2 presents the Beveridge curve for different thresholds K=10, 20, 30, 40, 50.

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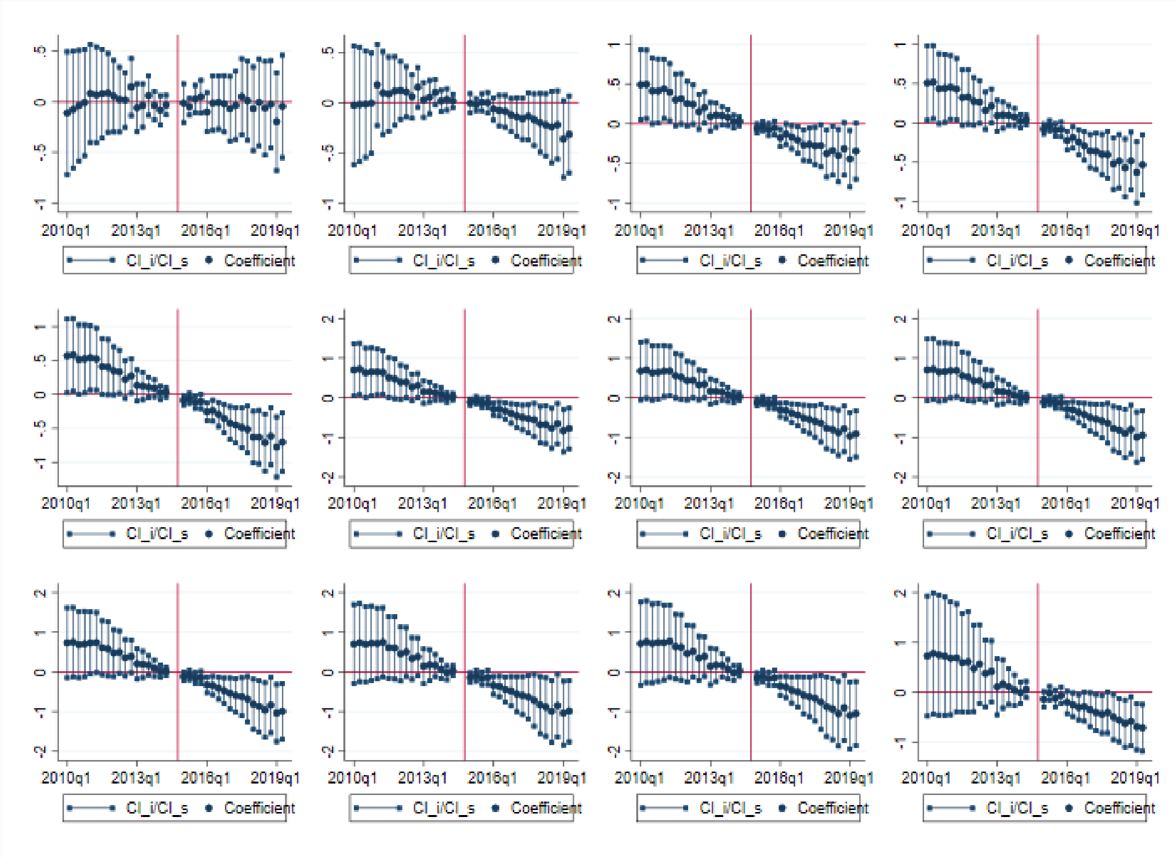

Notes: In the sub-panel of this graph, each of the interaction coefficients $\beta_{2,\tau}$ in equation (3) is represented. The interaction terms are the multiplication of treatment dummy with year-fixed effects. Confidence intervals are constructed at a 95% confidence level. In the regression, we control by time-fixed effects and by differentiated (cubic) time trends. From left to right and top to bottom, the values of each panel's thresholds are the following: K=2, 4,12, 16, 20, 24, 28, 30, 34,40,44, 48.


BANCO DE LA REPÚBLICA
COLOMBIA