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Content

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Abstract

This paper is the first to use program administrative data from Brazil's National Employment System (SINE) to assess the impact of SINE job interview referrals on labor market outcomes. Data for a five-year period (2012-2016) are used to evaluate the impact of SINE on employment probability, wage rates, time until reemployment, and job tenure. Difference-in-differences estimates suggest that a SINE job interview referral increases the probability of finding a job within three months of the referral and reduces the number of months to find reemployment, the average job tenure of the next job, and the reemployment wage. Subgroup analysis suggests that compared to more educated workers, SINE is more effective in helping less educated workers by increasing their probability of finding a job and reducing time until reemployment. Finally, the evidence suggests that online labor exchange is less effective than the service provided in person at SINE offices.

Keywords: employment agencies, labor market policy, employment services, labor exchange, job matching, job interview referrals, difference-in-differences.

JEL Classifications: J18, J23, J68.

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1. Introduction

Countries in the Latin America and Caribbean (LAC) region faced an array of labor market problems in the 1990s, including high unemployment, poor working conditions, and a lack of quality job opportunities. This situation generated policy interest in improving labor market programs, especially the public labor exchange. In recent years, labor market programs have garnered a bigger share of public resources in the region and have served more job seekers and employers since labor market policy has become an important macroeconomic policy instrument in the LAC region (Ramos, 2002).

In Brazil, even though labor markets have performed reasonably well over the past 15 years in terms of labor market participation and labor earnings growth, the unemployment rate increased from an average of 6.9% in 2011-2014 to an average of 12% in the last 4 years influenced by a recession that started in the second quarter of 2014.[1] The country's National Employment System (SINE) is a key institution in terms of public labor policies and can become even more relevant during economic downturns.

The SINE focuses on less educated and low skilled job seekers, but also provides services for customers who have higher education and job qualifications. This paper focuses on services to the majority of customers who have a history of job turnover in the formal sector and our subgroup analyses inform policy makers about the effectiveness of SINE for the full range of customers. Improving the SINE's ability to increase coverage to less skilled job seekers while improving SINE's services to more qualified job seekers could contribute to reducing the time it takes to fill vacancies. In Brazil it takes almost twice as long (9 weeks) to fill a skilled vacancy compared to LAC average (5 weeks) (Aedo and Walker, 2012).

As a percentage of the total budget for all active labor market programs, spending on labor intermediation services in Brazil is low compared to OECD countries. Brazil spends less than 2 percent of its active labor market program budgets on labor intermediation services delivered by SINE, while OECD countries spend an average of 10 percent of their active labor market program budgets on public labor exchanges (Silva et al. 2015, p 114). Since labor intermediation programs typically benefit low-skilled workers, countries with a larger proportion of these job-seekers could benefit from a larger investment.

[1] According to the Brazilian Business Cycle Dating Committee (CODACE) of the Brazilian Institute of Economics (IBRE), the recession lasted for 11 quarters, from the first quarter of 2014 to the last quarter of 2016.

Improving the efficiency of the public employment service (PES) is essential to support quick, successful, and high-quality job matches (Betcherman, Olivas, and Dar 2004). An effective PES contributes to labor-market efficiency and transparency, reducing informational imperfections that prevent the proper matching of jobseeker skills with employer job vacancies. Borges et al. (2017) estimate that PES labor intermediation in Brazil saved the Worker Protection Fund (FAT) budget about R$43 million in 2016 through reduced unemployment insurance (UI) payments. Since the PES provides services free of charge, it also improves equity in access to social participation through the labor market. Even though it is not an explicitly stated organizational objective, the PES potentially moves workers from informal to formal sector jobs that provide access to public health insurance and other benefits of activation. Finally, it is worth noting that even if labor intermediation does not have a significant effect on aggregate employment, it can help maintain the attachment of the long-term unemployed to the labor force, thereby decreasing their dependence on social assistance programs.

Considering the importance of public employment services, the paucity of research on program effectiveness in developing countries is remarkable. Among the studies conducted in the US and Europe, the evidence is consistently positive (Johnson et al. 1985; Katz 1991; Jacobson and Petta 2000; Blundell et al. 2004; O'Leary 2015, Warren and Klee 2017, Toohey 2017). While the estimated impacts on employment and earnings are typically small, the low cost of interventions often makes PES referral services cost-effective.

The few studies conducted in Latin America have had mixed results. Chacaltana and Sulmont (2003) find that the Peruvian PES more than tripled the probability of employment and increased earnings by 27 percent in the year after employment. On the other hand, Vera (2013) finds that participation in the PES in Peru lengthens unemployment spells by 33 days. Flores Lima (2010) finds no significant effects of the PES on the probability of finding a job in Mexico, but that the PES almost doubled earnings and tripled the rate of employment in formal sector jobs. Pignatti (2016) finds that using the Colombian PES increased the likelihood of having a formal job by between 5 and 31 percentage points but had a small negative effect on hourly earnings with declines ranging from 2 to 5 percent.

While program administrative statistics on labor intermediation in Brazil exist, to date there has not been a formal impact evaluation. This paper is a first step in that direction. The results of differences-in-differences estimations using microdata from 2012 to 2016 show that a job referral by SINE increases employment probability within the next 3 months and reduces the number of months until employment. However, SINE referrals are also estimated to decrease the average tenure and salary of the next job.

The remainder of the paper is structured as follows. Section 2 provides a background of related literature. Section 3 presents a description of the data and descriptive statistics. Section 4 presents the methodology, and Section 5 presents results. Section 6 presents concluding remarks.

2. Background

Previous related research literature reports mixed evidence on the effectiveness of work intermediation programs. Evaluations of the PES have focused mainly on the impacts on employment probability, unemployment duration, and earnings. Specifically, some papers attempt to estimate national average employment impacts. The earliest attempts to assess the impact of PES are found in the United States in papers by Johnson et al. (1985) and Katz (1991). Johnson et al. evaluate the effect of referrals to job interviews made by local offices of the U.S. Employment Service (ES), comparing the employment and earnings outcomes of those referred to job interviews to ES registrants who were not referred. The authors find significant positive effects on women's return to work, including the probability of employment six months after the job interview referral, the probability of remaining in the labor force, and earnings. However, the effect of an ES job interview referral for men was insignificant. The authors suggest that this result can be explained by the barriers women face in accessing other job finding methods.

Katz (1991) analyzed the role of ES in assisting dislocated workers in Pennsylvania who remained jobless for extended periods of time. Dislocated workers were defined as those who received UI benefits, had strong job attachment, and did not have a job in the quarter immediately prior to applying for UI. Katz finds that the effectiveness of the ES was dependent on the duration of unemployment. While job search assistance from the ES was more effective at the beginning of unemployment, job placements and referrals to job interviews had bigger effects on reemployment a few quarters later.

Jacobson and Petta (2000) find that ES job placements in Oregon and Washington State are most effective for those with strong previous job attachments. Specifically, the authors find that placements reduced the duration of insured unemployment in both states, and even job interview referrals that did not directly lead to job placements reduced the claimants' duration of UI benefits received in both states. If an increase in employment among people who receive public employment services is achieved at the expense of job seekers who did not receive services, then displacement has occurred. However, in cases where the PES facilitates a small percentage of labor market placements, as in Brazil where only 3% of placements are made by SINE, displacement effects are unlikely to be a serious issue.

A European study by Launov and Wälde (2016) uses the Mortensen-Pissarides matching model, finding that an increase in operating effectiveness by the German public employment agency reduced unemployment nationwide. Notably, this reform turned out to favor long-term unemployed workers at the expense of newly unemployed workers, even though the long-term unemployed are regarded as particularly difficult to serve.

Crépon et al. (2013) measure the impacts of job placement assistance on the labor market outcomes of young, educated job seekers in France. They find that even though the program increases the likelihood of finding a stable job in France, the positive effect diminishes over time, and often comes at the expense of other eligible workers. Crépon et al. (2013) suggest that French job placement assistance had little net effect on overall unemployment in the country.

Blundell et al. (2004) use difference-in-differences (DID) to analyze the impact of the "New Deal" for Young People in the UK, a compulsory program aimed at helping young people to claim unemployment benefits for at least six months. The program offers job assistance for four months and a wage subsidy paid to employers. The authors find that the program increased the probability of young men finding a job in the next four months by 5 percentage points. This impact was larger at the beginning of the New Deal program.

Other studies compare the impacts of publicly and privately delivered employment services. For example, Behaghel et al. (2014) compare the effectiveness of an intensive program provided by the public employment agency and private contractors in France. The study concludes that the publicly provided services had greater and faster impacts on exit to employment than private services. In contrast, Vera (2013) finds that the Peruvian PES had smaller impacts on unemployment spells compared to alternative job search methods (e.g., private agencies). The author cites factors that may reduce coverage and lessen the effectiveness of the program, such as informal labor markets, low use by highly skilled persons who normally work in salaried employment, high labor turnover, lack of unemployment benefits, and little confidence in public sector institutions.

Pignatti (2016) estimates that the Colombian PES has a positive effect on the probability of getting a job in the formal sector when services are provided face-to-face (i.e., in PES centers) rather than online. The results suggest that the effects on formality come from professional labor market matching in face-to-face services provided by the PES. The author also finds that using the Colombian PES positively impacts the probability of having a formal job, and that this effect is due to the program's capacity to place job seekers in large companies. On the other hand, the results show that getting a job through the PES in Colombia has a negative effect on earnings. Pignatti's work is particularly relevant to our research, because it analyzes the effectiveness of the PES for subgroups of service recipients in a Latin America context. However, it is important to note that Pignatti's data is based on a sample of PES users from a general household survey that does not have a panel structure and does not provide detailed information on previous job search history.

Our paper uses the full population of PES users in Brazil merged to RAIS (Relação Anual de Informações Sociais—Annual Social Information Report) longitudinal data on employment and earnings and is, to our knowledge, the most complete evaluation of labor intermediation conducted in Latin America. Therefore, while Pignatti's analysis cannot directly investigate the effects of program participation on the probability of finding a job, we are able to do so, since our unique dataset allows us to follow job seekers' labor history, prior to and following the SINE job interview referral.

Only one prior study has attempted to assess the effectiveness of job interview referrals on different groups of participants in Brazil. Woltermann (2002) finds that the only significant channels for a transition into formal sector jobs were: directly contacting the employer, using connections through family and friends, and responding to advertisements. Nevertheless, the study is based on the Monthly Employment Surveys (PME) collected by the Brazilian

Institute for Geography and Statistics (IBGE) and does not include data from Brazilian employment services.

Thus, the existing literature does not provide a comprehensive impact evaluation of the effectiveness of labor intermediation programs on employment probability, earnings, time until reemployment, and job tenure in Latin America. This paper provides the first attempt to understand the effectiveness of such important nationwide active labor market programs in the Latin American context using data from Brazil.

3. Data and Descriptive Statistics

We constructed a unique dataset merging administrative data from the SINE with data from the RAIS to analyze the effectiveness of labor intermediation in Brazil. The SINE was established in 1975 as a public agency for labor market programs, including the labor exchange. Its original purpose was to promote labor intermediation, but currently its services include professional orientation, referral to qualification and training programs, job placement, labor market information, issuance of formal workers identification credentials, and managing some components of the UI program including payment of benefits.[1]

The intermediation process involves the registration of workers and employers, recording information on the employment histories of job seekers, and solicitation and listing of job vacancies. It also entails the matching of job seeker profiles with the requirements of vacancies, summoning and referring workers to interviews based on the matching results, and capturing referral outcomes. SINE's intermediation service also involves the management of job vacancy listings from the moment they are received to the moment they are filled or expired. The SINE database contains socioeconomic information on workers from registration (age, gender, education, and employment status), employers, and records of available job vacancies and job interview referrals (status of the referral, employer feedback, and type of service offered). The SINE database includes the unique individual identification number *Cadastro de Pessoas Físicas* (CPF) and allows us to track job-seekers during the period of analysis.

[1] See the following website for more details: http://portalfat.mte.gov.br/programas-e-acoes-2/sistema-nacional-de-emprego-sine/

The SINE data are complemented by the RAIS annual administrative dataset compiled by the Labor Ministry of Brazil, containing employment and earnings information on all formal firms and employed workers in a given year.[2] All formally-registered firms in Brazil report annual information on their employees. The RAIS includes detailed information on the employer, the employee, and the employment relationship (wage, tenure, type of employment, hiring and separation date, reason for separation, among others). Importantly, RAIS is a linked employer-employee matched dataset that can be linked to the SINE dataset using CPF.

For this paper, the RAIS data are available from 2011 through 2016. The RAIS dataset is structured such that each observation represents an employment relationship containing the dates of hiring and separation. We use these data to construct a monthly panel with information on each individual's employment status in each month. Our aim is to analyze exit from unemployment of workers with recent experience in formal sector jobs. The panel data allows us to observe workers with more than one job at the same time–i.e., multiple job holders. Since job loss for a multiple job holder does not result in full unemployment, our sample excludes workers who at some point had multiple simultaneous formal sector jobs.[3] Since most workers who seek SINE's assistance are unemployed (94%), we restrict the analysis to workers who were separated from their job at some point before a job interview referral. In the panel using information from the RAIS, a period between jobs in RAIS is a period of non-employment in the formal sector. Using the information from the separation and hiring dates in RAIS, we create a panel of individuals with formal employment history and at least one non-employment spell in the formal sector.[4]

We observe that a person who gets a referral in 2012 has a 90 percent probability of finding a formal job within the next 5 years. This means that restricting the panel to workers with at least one unemployment spell and a registry of formal employment after being referred to a job interview by SINE retains most of the observations in our panel.[5]

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[2] Severance payments are based on RAIS records; thus, employers and workers have a strong incentive to submit the annual RAIS declaration. The Ministry of Labor estimates that RAIS coverage represents about 97% of the formal sector.
[3] Simultaneous jobs are defined as two or more jobs with durations (start and end dates) overlapping in time. This guarantees the fulfillment of the assumption that the period following a dismissal is, in fact, a non-formal employment state.
[4] RAIS data includes formal sector workers. We refer to non-employment in the formal sector as unemployment.
[5] This is unlikely to be an issue even for the last year of data, about 43% of workers who got referral in 2016 get a job in the same year.

Taking these restrictions into account, the study addresses unemployed individuals who were never multiple job holders in the period analyzed, but who had at least two jobs in the RAIS, one before and one after a job interview referral. We make this sample restriction because only the RAIS data allows us to calculate the outcomes, and only the workers with a formal job history are included in this database. The unemployment (or non-formal employment) periods correspond to individuals who were hired at some point in the panel after being separated. The resulting panel includes 30 million unemployment spells, 29 million workers, and about 5 million individuals per month before the matching. In this data, about 65,000 job interview referrals are observed each month. The average job tenure in the data is about two years, suggesting that the 5-year available time spam used in the paper is not short and that monthly analysis is required for short average job tenures.[6]

Combining the SINE and RAIS datasets allows us to trace the duration of formal employment, time until reemployment, and earnings in the new job for individuals who look for employment through SINE agencies compared to those who use other job-search methods. Table 1 provides descriptive statistics on the labor intermediation activities of SINE between 2012 and 2016. We chose this period because a new data system was established in 2012 and the quality and reliability of data improved significantly from that time onward according to the Ministry of Labor. Table 1 shows, the total number of unique workers registered in the SINE system reached 31.7 million in the 2012 to 2016 period.[7] While 70% of the vacancies[8] available at SINE have at least one job interview referral, only 28% of the vacancies are filled through a SINE job referral. The overall placement rate (workers placed by referral) of SINE is about 12% throughout the period of analysis. Note that online self-service referrals were permitted starting in 2014.

[6] The average job tenure for the formal private sector in Brazil is about 3.5 year according to DIEESE (2016).
[7] Table 1 shows the number of new SINE registrants per year. For instance, in 2016, 4,587,164 workers that had never registered with SINE made their registration. Thus, 31.7 million is the number of unique workers registered.
[8] In the SINE system, one "vacancy" posted by an employer might represent more than one position. For instance, a firm might submit one "vacancy" requiring 10 employees. On average, 3.8 positions are offered per each SINE "vacancy." This average increases to 5.4 positions per vacancy when taking into account only the vacancies that were filled with at least one position.

Table 1

Descriptive Statistics of SINE Labor Intermediation

Year of first registration	Workers registered	Vacancies	Referrals	Workers placed	Placement rate %	Online referrals
2012	8,231,696	3,072,010	5,941,732	731,177	12%	0
2013	7,480,241	3,597,192	6,747,252	838,772	12%	0
2014	6,232,876	2,715,616	5,836,580	686,605	12%	152,968
2015	5,185,316	1,758,888	4,901,468	616,745	13%	243,265
2016	4,587,164	1,151,366	3,784,249	402,517	11%	211,955
Total	**31,717,293**	**12,295,072**	**27,211,281**	**3,275,816**	**12%**	**608,188**

Source: Own calculation, based on data from the Ministry of Labor. Placement rate= ratio of workers placed to referrals.

To evaluate the impact of labor intermediation, we construct a monthly database with matches of referrals to non-referrals. The data matches only one referral each month per individual, even if that individual was referred more than once in a month.[9]

Table 2 shows that 94% of the referrals are made for unemployed job seekers, which is the group of workers analyzed in this study.[10] The average age of the workers referred by SINE is higher for the unemployed than for the employed, and the difference is around 7 years between the two groups. The total mean age of all the SINE applicants is about 30 years old. While almost 50% of the workers are high school graduates, only 11% have some college education. Finally, 58% of the registrants are male and 61% are considered non-white.

[9] The placement rate (workers placed by referral) that considers one referral per month is higher (16%) because the number of workers placed remains the same, but the number of referrals is lower than listed in Table 1 (see Appendix A1).
[10] The relative number of matches is higher for employed jobseekers, with 19% of effectiveness, compared to 12% of placed workers on referrals made on the unemployed. This means that the chance to get a job might not only depend on the skills of job seekers, but also may be related to other aspects such as their employment status (Appendix A, Table A2).

Table 2
Descriptive Statistics for Job Seekers Referred by SINE, 2015

	Observations	
	Employed	**Unemployed**
% Observations	6%	94%
Age Sample Means	24,1	31,7
Race		
Indigenous	0%	0%
White	38%	42%
Dark	11%	12%
Yellow	1%	1%
Brown	49%	45%
Education		
Illiterate	0%	0%
Middle school	9%	15%
Middle school graduate	6%	11%
High school dropout/incomplete	29%	14%
High school graduate	46%	49%
College dropout/incomplete	7%	7%
College graduate	2%	3%
Specialization	0%	0%
Advanced degree/PhD	0%	0%
Gender		
Male	48%	58%
Female	52%	42%

Source: Authors' calculation based on data from the Ministry of Labor

Brazil is well known for having wide regional variation in cultural and economic matters, which extends to the SINE system. Therefore, in estimating program effects it is important to control for differences across states. Table 3 illustrates the heterogeneity across Brazilian states. The state of Paraná lists the highest ratio between vacancies per registered job seeker (77.5%) and the most vacancies per SINE office (16.720). However, the placement rate of the Paraná SINE offices is only 14.8%, since it has the second most job seekers per office (21.587) and makes the most job interview referrals per office (44.362). In contrast, Alagoas, with a lower ratio of vacancies per registered job seeker (35%), has the highest rate of job placements (46%) perhaps due to a rate of referrals per office (4.316) that is only one-tenth the rate in Parana and the Federal District. Even though São Paulo, the richest and most populous state in the country, offers the second most vacancies per labor intermediation office (13.998), it has a placement rate below the national average (7.2%). São Paulo had more than 10 million registered job seekers in the period, meaning each agency must serve more customers on average (31.889) compared to other states, which leads to a modest rate of vacancies per job seeker (44%) and a very high number of job referrals per office (27,270). The richness of the data available allows us to control for heterogeneity in labor markets as explained in the next section.

Table 3: Descriptive Statistics of SINE Labor Intermediation by State, 2012-2016

State	Workers registered (1,000)	Offices per State	Vacancies	Vacancies per registered (%)	Registered workers per office	Vacancies per office	Referrals per office (1,000)	Placements per office (1,000)	Placement rate (%)
Acre	80,247	11	137,497	11.0	7,295	803	2,008	395	19.7
Alagoas	393,550	43	49,209	34.9	9,152	3,198	4,316	1,984	46.0
Amapá	83,460	12	643,526	15.2	6,955	1,056	1,461	118	8.1
Amazonas	453,945	29	140,717	31.0	15,653	4,852	5,074	1,428	28.1
Bahia	1,859,443	149	79,584	30.3	12,479	3,785	9,216	1,962	21.3
Ceará	931,723	135	563,919	69.1	6,902	4,767	10,014	2,870	28.7
Dist Federal	501,929	26	250,436	46.6	19,305	8,995	41,793	2,492	6.0
Espírito Santo	642,186	34	8,832	28.8	18,888	5,442	11,152	792	7.1
Goiás	1,150,209	90	139,568	36.4	12,780	4,658	11,468	1,005	8.8
Maranhão	552,293	47	1,454,639	8.9	11,751	1,047	1,990	674	33.8
Mato Grosso	569,393	45	52,050	44.0	12,653	5,565	10,416	2,067	19.8
Mato Gr do S	442,099	40	198,142	44.8	11,052	4,954	14,060	2,060	14.7
Minas Gerais	3,066,879	227	33,474	26.8	13,510	3,620	11,275	1,048	9.3
Pará	832,355	56	99,891	9.6	14,863	1,421	2,125	488	23.0
Paraíba	430,538	40	9,081	23.2	10,763	2,497	5,207	716	13.8
Paraná	1,878,055	87	289,921	77.5	21,587	16,720	44,362	6,583	14.8
Pernambuco	977,721	82	662,611	29.7	11,923	3,536	9,155	1,109	12.1
Piauí	307,818	31	1,013,274	10.9	9,930	1,080	1,843	254	13.8
Rio de Janeiro	2,362,499	127	324,924	42.9	18,602	7,979	8,708	922	10.6
Rio Gran do N	379,473	38	821,631	9.5	9,986	0,951	2,307	195	8.5
Rio Gran do S	1,791,515	128	419,242	37.0	13,996	5,177	14,273	1,519	10.6
Rondônia	234,515	20	36,130	22.2	11,726	2,603	6,221	921	14.8
Roraima	61,362	7	12,673	14.8	8,766	1,297	5,880	800	13.6
Santa Catarina	1,183,483	74	25,949	27.5	15,993	4,391	9,947	1,026	10.3
São Paulo	10,045,183	315	4,409,235	43.9	31,889	13,998	27,270	1,970	7.2
Sergipe	29,309	21	185,039	8.9	13,957	1,236	3,100	245	7.9
Tocantins	212,324	16	233,878	65.7	13,270	8,723	22,394	4,002	17.9
Total	**31,717,287**	**1,930**	**12.295.072**	**38.8**	**16,434**	**6,371**	**14,098**	**1,697**	**12.0**

Source: Authors' calculation based on data from the Ministry of Labor

4. Methodology

4.1. The evaluation

The purpose of this paper is to estimate the effects of SINE job interview referrals on labor market outcomes. That is, we analyze the effect of referrals by SINE offices on labor market outcomes of participants compared to non-participants. However, simple differences of means between participants and non-participants will not yield reliable estimates of program effects because the characteristics of the two groups are likely to be different due to self-selection into SINE registration and services. Thus, we compare the outcomes of two groups, one given the treatment and one not given the treatment to serve as a baseline reference.

The evaluation problem is to compare participants to themselves with and without the service. However, we do not observe the outcome for service recipients had they not received the service. To measure SINE's impact, we must construct comparison groups of non-participants with similar average characteristics as the program participants. In this study, we use Propensity Score Matching (PSM) to construct comparison groups and then estimate group mean effects or the average treatment effect. The individuals in the matched comparison group will be similar to the participants in observed characteristics, except for the referral. To this end, we construct a counterfactual for the treated by selecting a group of non-participants who have a similar pre-treatment conditional probability of receiving a treatment.

The propensity scores used to balance characteristics between participant and non-participant groups is estimated by the following probit model for each subgroup evaluated:

$$\begin{aligned} \mathrm{P}(D=1|X) = \beta X &+ \gamma_1(Age + Job_{tenure} + log(wage) + Gender)D_{state} \\ &+ \gamma_2(Age + Job_{tenure} + log(wage) + Gender)D_{month-year_{separat}} \\ &+ \epsilon \end{aligned} \tag{1}$$

In this specification, we calculate the probability of being referred for a job interview P(*D=1|X)* as a function of observable individual characteristics. Importantly, our data includes successive monthly cohorts of participants and their counterfactuals between January 2012 and December 2016. Job interview referrals are measured on a year-month reference basis.[11] Using these monthly samples of participants and non-participants, we estimate sixty PSM models. That is, we estimate one PSM model for each month in our panel. We follow the approach of Sianesi (2004) who estimates separate PSM models for each month in her panel data. We use nearest neighbor matching without replacement to create comparison groups. Individuals are matched with certainty on two characteristics: number of months unemployed until matching and the workers' state of residence. Each treated individual is matched with a non-treated individual from the same state, someone who has the exact number of months unemployed until the matching.[12]

The remaining observable individual characteristics in the vector X for the PSM are: tenure of the last job before referral (months), the logarithm of the average monthly salary on the last job, race (divided into 5 categories: indigenous, white, dark, yellow, and brown), age in the year of the matching, gender, educational attainment (divided into 11 categories), industrial sector (86 categories of CNAE[13] at 2 digit-level) and occupational group (48 categories of CBO[14] at 2 digit-level) in their last job. In addition, as shown in equation (1), the following interactions are included to improve matching quality: age, job tenure, wage, and gender interacted with the state dummies and with month/year dummies of the worker's separation.[15]

We use two strategies to construct control groups based on the probability of being referred for a job interview. First, we construct control groups using the pool of workers that registered at a SINE office but were not referred for a job interview. This approach mitigates selection bias, since workers who visit a SINE office might be self-selected and expose themselves to the treatment for several non-observable characteristics, such as level of self-motivation and general proactiveness. Alternative control groups are constructed based on a broader pool of workers available in the RAIS at any point of our panel who were not referred for job interviews using SINE services. These control groups are more subject to selection bias, as

[11] In other words, we count referrals and registrations in a given month only once.

[12] Lechner (2002) also matches with a mixture of exact characteristics and propensity scores, matching exactly on sex, duration of unemployment, and native language. Lechner also uses propensity scores in an evaluation of active labor market programs in Switzerland.

[13] CNAE is the national classification of economic activities.

[14] CBO is the Brazilian classification of professions.

[15] Heinrich et al., (2010, IDB) suggest that interacting vector X with state and month improves the matching model. We apply a simplified PSM to subgroup analyses, where fewer observations are available (education, age group, SINE WEB, gender, and unemployment insurance) to improve efficiency in terms of processing time and to maintain the quality of the matching. In order to simplify the probit model, we eliminate variables that are not significant and reduce the number of interactions. For the exact matching, only region was used, and time until matching became a control in the regression. The specification for the simplified probit is the following:

$$P(Y) = \beta X + \gamma(Age + Job_{tenure} + log(wage) + Gender + time\_until\_match)D_{region} + \epsilon$$

most workers who are in RAIS do not visit a SINE office.[16] Thus, our main results are based on the control groups applying the first strategy. Additionally, we require the common support condition to be met exactly. Results using alternate control groups constructed using RAIS are presented in the Appendix C.

After estimating propensity score models, the next step is to perform the matching and assess its quality. The literature suggests that observable characteristics should be balanced between the two groups after matching. As the matching is performed monthly, the balance in the means of basic obervable characteristics must be checked for each month. Table 4 shows the t-tests for differences in means before and after the matching for certain characterictics in November 2016. The bias for a given variable is defined as the difference between the means of participant and comparison groups scaled by the average variance. A bias reduction after the matching is expected after matching. The t-tests show that before matching, the participant and comparison groups are sigificantly different on most observable characteristics, but after the matching there are very few significant differences. This suggests that the participant and non-participant matched samples are well balanced.

[16] The information used in the PSM to construct control groups always comes from RAIS. What differs is that the first strategy to construct control groups uses only workers registered at SINE, while the second strategy uses the broader pool of workers from RAIS who did not visit a SINE office. While the main database used to compare the referred vs. non-referred individuals was the SINE, information from the RAIS was essential to calculate PSMs and measure the outcomes, since it allowed us to track the employment history of each job seeker.

Table 4
Descriptive Statistics Pre- and Post – Matching
Treatment: Referrals | Control Group: SINE
November 2016

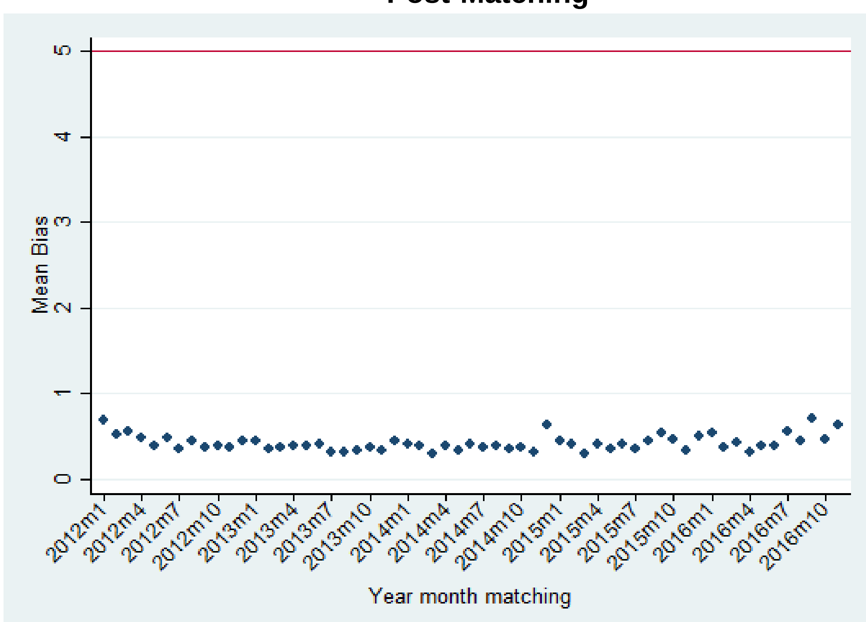
Variable	Sample	Mean		%Bias	% Bias Reduction	t-test	P>|t|
		Treated	Control				
Male	Unmatched	0.606	0.590	3.16%		2.386	0.017
	Matched	0.586	0.597	-2.15%	31.9%	-1.002	0.316
Age	Unmatched	31.583	29.038	24.58%		18.418	0.000
	Matched	28.341	28.605	-2.69%	89.1%	-1.254	0.210
Tenure last job	Unmatched	19.399	17.846	5.94%		4.424	0.000
	Matched	13.208	13.057	0.75%	87.4%	0.348	0.728
Mean wage last job	Unmatched	7.180	7.159	4,30%		3.184	0.001
	Matched	7.107	7.130	-5,09%	-18,2%	-2.374	0.018
White	Unmatched	0.459	0.461	-0.56%		-0.426	0.670
	Matched	0.481	0.470	2.25%	300.3%	1.051	0.293
Illiterate	Unmatched	0.002	0.003	-2.66%		-1.973	0.048
	Matched	0.002	0.002	0.00%	100.0%	0.000	1.000
Elementary incomplete	Unmatched	0.023	0.030	-4.65%		-3.484	0.000
	Matched	0.021	0.023	-1.25%	73.1%	-0.584	0.559
Elementary complete	Unmatched	0.027	0.027	-0.34%		-0.254	0.800
	Matched	0.027	0.027	0.43%	-26.6%	0.198	0.843
Middle incomplete	Unmatched	0.078	0.081	-1.12%		-0.845	0.398
	Matched	0.074	0.070	1.87%	-66.8%	0.871	0.384
Middle complete	Unmatched	0.126	0.116	2.88%		2.186	0.029
	Matched	0.121	0.121	-0.14%	95.1%	-0.066	0.948
High school incomplete	Unmatched	0.118	0.166	-13.91%		10.418	0.000
	Matched	0.154	0.140	4.15%	70.2%	1.936	0.053
High school complete	Unmatched	0.575	0.484	18.31%		13.842	0.000
	Matched	0.541	0.555	-2.77%	84.9%	-1.291	0.197
College incomplete	Unmatched	0.027	0.030	-2.36%		-1.775	0.076
	Matched	0.028	0.032	-2.43%	-3.0%	-1.133	0.257
College complete	Unmatched	0.025	0.060	-17.34%		12.754	0.000
	Matched	0.031	0.031	-0.13%	99.2%	-0.062	0.951
Master	Unmatched	0.000	0.001	-3.47%		-2.481	0.013
	Matched	0.000	0.000	2.14%	38.3%	1.000	0.317

Source: Authors' calculation based on data from the Ministry of Labor

The matching does not necessarily need to be balanced in all variables to be satisfactory, and we use the mean standardized bias to formally assess the quality of the PSM.[17] If observable characteristics are balanced between the control and treatment groups after matching, it is expected that the mean standardized bias between control and treatment groups will be significantly reduced. According to empirical studies, a final bias below 5 per cent (red line in Figure 1) after matching should be sufficient (Caliendo and Kopeinig, 2008). Each dot in Figure 1 represents the average of the standardized bias of the mean on all exogenous variables (used in the PSM) calculated for each month separately. In this case, the bias maintains an average value of 0.5 after the matching.

An additional step to verify the matching quality is to examine the kernel density distribution graphs of the propensity score for the two groups before and after the matching– see Figures B1 and B2 in Appendix B. These figures show that there is an overlap in the mean propensity scores and their distributions for the two groups after matching, suggesting that the PSM generates good matches.[18]

Figure 1
Mean Standardized Bias Between Control and Treatment Groups Post-Matching



[17] We use other tests to assess the quality of the matching. The Rubin R (the ratio of treatment variance to control variance, which must be close to 1) and the Rubin B (the number of standard deviations between the means of the groups, which must be less than half a standard deviation) are tested and their results confirm the matching quality (see Figures B3 and B4 in the Appendix).
[18] The PSM is conducted for each month of our panel and the kernel densities present a similar pattern in every month. Monthly results are available upon request.

We use the participant and comparison groups constructed by propensity score matching to measure impacts on the following labor market outcomes: employment, time from registration until employment, job tenure, and reemployment monthly earnings. As described in Section 3, to perform the matching we restricted the database to workers who lost their job and obtained a new one, which allows us to calculate the pre- and post- matching variables. Details on the calculation of the resulting outcomes (pre- and post- treatment) are provided below.

4.2. Measuring SINE impact on labor market outcomes

Having constructed counterfactual groups for workers who had a SINE job interview referral through propensity score matching, which was validated by three tests, we use the constructed counterfactual groups in the following DID specification to estimate the impact of a job interview referral on labor market outcomes for worker *i*:

$$Y_{it} = \varphi + \alpha Treated_i + \gamma Post_{it} + \theta SINE_i + \beta X_i + \mu_t + \varepsilon_{it} \qquad (2)$$

where Y_{it} stands for one of the four outcome measures for individual *i* and time *t*. *Employment within 3 months of referral* establishes whether at the month of the matching the worker got a job within 3 months of the referral. In the evaluation, this variable is always 0 for the pre-matching period.[19] *Time until employment* is unemployment time between jobs, calculated as the date of admission to the next job minus the date of separation from the previous job.[20] *Mean tenure* is the tenure of the last job before the matching or the first job after the matching, accordingly. The sample is restricted to workers who lost their job after the matching, so that the variable is not censored, and *Reemployment wage* is based on the natural logarithm of real wages of the last job before and after the matching.

The term φ captures all time-constant factors that affect the outcome. $Treated$ is a dummy variable indicating whether the individual gets a SINE job referral or not, and *Post* takes the value of one after treatment. The variable SINE is the interaction between $Treated$ and *Post*

[19] To evaluate this outcome, we remove matches from September 2016 onwards in order to leave only observations that are well defined (individuals that possess at least 3 months of information for this outcome).
[20] The sample of this database is especially restricted, because it requires each worker to have at least 3 jobs in the panel to allow for unemployment time between jobs before and after the treatment.

and θ, the coefficient of interest, measures the difference in the outcome variable between the treated and control groups before and after receiving services from SINE. μ_t are the monthly dummy variables. The matrix X includes alternative education and sector variables for individual workers who are not included in the PSM.[21] We also include information on whether the worker is a beneficiary of UI, dummies for the n^{th} UI payment, and total number of referrals.[22]

5. Results

5.1 Overall Results

The analysis compares the effect of referrals on the probability of workers finding a job within three months of the referral, time until employment, the mean tenure of the next job, and the reemployment salary when comparing to workers who were registered at SINE but did not get a job referral.[23]

The results in Table 5 show that the treatment increases the likelihood of finding a job within three months of the referral by 19.7 percentage points (pp). In addition, job seekers who are referred by SINE take less time (0.8 months) to find a job. SINE job referrals have a negative impact on the mean tenure of the next job found; on average it is reduced by 4.1 months. Finally, being treated by SINE reduces wages by about 3.5 per cent.[24] This result is consistent with Pignatti (2016) and Vera (2013) and might be related to stigmatization effects on SINE participants or the lack of capacity of the program to attract high-paying enterprises in the system.[25] The estimated effects are the average for the period of analysis and because of the short job tenure duration and high worker turnonver in the Brazilian labor market, the 5-year time spam is enough to provide results about how SINE affects labor market

[21] Education is disaggregated into 3 categories: unskilled (from illiterate to complete primary school), semi-skilled (incomplete and complete high school), skilled (from incomplete undergraduate education to PhD). The sector of last job from the IBGE Classification is aggregated in the following categories: agriculture, industry, services, trade, construction and other).

[22] These variables are included in the difference-in-difference estimations as they were not available when the PSM were calculated. Difference-in-difference estimations without the variables included in vector X provide similar results.

[23] Results using RAIS for control groups are very similar and are provided in Appendix C.

[24] Appendix D provides an indication on the size of SINE's impact on outcomes. For instance, 0.39 percent of workers in the control group obtained a job within three months after matching and SINE increased this probability by 0.19 pp.

[25] We used PSM to match firms that posted vacancies at SINE and firms that did not in 2015. Matching variables were the proportion of males, proportion of white workers, average worker age, firm size, sector classification and state of the firm. This exercise suggests that wages at firms that post vacancies at SINE is 140 Brazilian Reais lower than a similar firm that does not post vacancies at SINE. The results that SINE referrals decrease the time to re-employment but also reduce the time of employment and salary needs further investigation as getting a job faster may be related to a worse quality of the matching, nevertheless, the overall data does not provide a clear correlation between time until employment and tenure and salary.

outcomes.[26] Subgroup analysis based on workers' characteristics are provided in the next section.

Table 5
Effect of SINE Referrals

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment Wage (log)
Control group from SINE	0.197*** (0.00798)	-0.886*** (0.111)	-4.114*** (0.215)	-0.0351*** (0.00858)
Observations	14,447,964	6,519,222	11,227,510	14,519,093

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2 Demographic Subgroups

Subgroup estimations are important in identifying heterogenous effects of SINE services and in guiding the strategy to provide services for workers with different characteristics. For each subgroup, we calculate a specific PSM for each of the 60 months of the data and estimate the corresponding DID.[27]

Results dissagregated by gender are presented in Table 6 and go in the same direction as the overall estimations provided in Table 5. Nevertheless, the impact of an interview referral is different for women and men, which indicates that the effectiveness of SINE might differ according to gender. SINE increases the probability of finding a job within 3 months by 23 percentage points for men and 21 percentage points for women. Reemployment wage is reduced by 4% for men and 5% for women when reeemployment is found through SINE. On the other hand, SINE reduces women's time until employment by 1.8 months while the effect on men is a reduction in time until employment of 1.4 months.

[26] Appendix E (Table E.1) provides similar results using only data for referrals made in 2012, which allows the effects of SINE to be measured in a longer time span.

[27] The effects across groups and overall effects are not directed compared as the DID estimations and PSMs are conducted separately for each subgroup (i.e., comparing women who get interview referrals to women who did not get interview referrals) to allow for the best matching and estimations against each control group. Alternative results for the full model based on one general PSM and estimating subgroup effects in the same regression are provided upon request. Complete models are estimated for gender, education, age, race, and receipt of unemployment insurance. Estimating coefficients in the same regression allows for a better comparison across different groups and tests of the equality of coefficients; however, it provides poorer matching, as those treated in subgroups might be matched with a control that belongs to another subgroup.

Table 6
Effect of SINE Referrals
Gender

	Employment within 3 months	**Time until employment (months)**	**Mean tenure (months)**	**Reemployment Wage (log)**
		MALE		
Control group from SINE	0.228***	-1.354***	-2.412***	-0.0431***
	(0.00707)	(0.070)	(0.334)	(0.00885)
Observations	8,984,312	4,845,822	6,573,682	9,032,520
		FEMALE		
Control group from SINE	0.210***	-1.791***	-2.462***	-0.0517***
	(0.00822)	(0.0557)	(0.233)	(0.00694)
Observations	6,205,148	2,637,852	4,329,852	6,243,483

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Most workers who seek SINE's support (90%) have up to completed secondary education. Understanding the heterogenous impact of the labor intermediation across workers with diffferent levels of education is important. Education is disaggregated in 3 categories in Table 7: unskilled (from illiterate to complete primary school), semi-skilled (incomplete and complete high school), and skilled (from incomplete undergraduate education to PhD). Most of the applicants (80%) are considered semi-skilled, while only 10% are skilled. The magnitude of the effect of referrals on the probability of finding a job within three months decreases as the years of education increase, which means that SINE increases the probability of the less skilled applicants of getting a job (compared to non treated less skilled) more effectively when compared to the group of most skilled workers. Also, the lower wage effect of the SINE referrals compared to the non-referred is stronger on the most skilled applicants. Specifically, while unskilled job seekers referred by SINE see a salary drop of 1%, the semi-skilled receive a salary decrease of 5%, and the skilled workers see a 22% drop in their salary. The negative effect on the wages of the highly-skilled might signal a SINE incapacity to attract high-quality vacancies. Unskilled applicants referred by SINE reduce time until employment by 1.2 months, and this reduction is 1.0 and 0.9 months for semi-skilled and skilled job seekers, respectively. Also, SINE reduces the job tenure of unskilled workers by 1.3 months and the impact is more pronounced and job tenure is reduced by 1.6 months for semi-skilled and 2.4 months for skilled applicants with job referrals.

Table 7
Effect of SINE Referrals
Education

	Employment within 3 months	**Time until employment (months)**	**Mean tenure (months)**	**Reemploymen t wage (log)**
		UNSKILLED		
Control group from SINE	0.247*** (0.00978)	-1.198*** (0.140)	-1.259*** (0.318)	-0.00864 (0.00695)
Observations	4,079,672	2,003,960	3,167,676	4,090,869
		SEMI - SKILLED		
Control group from SINE	0.212*** (0.0080)	-1.054*** (0.0499)	-1.567*** (0.212)	-0.0464*** (0.00533)
Observations	20,231,684	9,635,912	14,431,970	20,351,358
		SKILLED		
Control group from SINE	0.186*** (0.00933)	-0.934*** (0.112)	-2.438*** (0.209)	-0.223*** (0.0122)
Observations	982,852	465,446	424,462	990,942

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 reports that the size of the positive effect of SINE referrals on the time to find a job diminishes as workers age: the group between 18 and 24 years old takes 1.5 fewer months to get employed than the control group, while the group between 45 and 54 years old takes 0.45 fewer months, and the oldest group (between 55 and 64 years) presents a reduction of 0.35 months compared to the control group, which is less than half the effect of the referrals on the youngest group. In contrast, the negative effect of the referrals on the next job duration is more significant among the eldest groups, which presents the greatest reductions in their tenure (up to 2.6 months for the 55-64 year old group).

Table 8
Effect of SINE Referrals
Age

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment wage (log)
		AGE 18-24		
Control group from SINE	0.210***	-1.493***	-0.740***	-0.0474***
	(0.0101)	(0.0409)	(0.0568)	(0.00354)
Observations	7,933,844	3,587,946	5,956,018	7,994,660
		AGE 25-34		
Control group from SINE	0.223***	-0.923***	-1.560***	-0.0525***
	(0.00734)	(0.0436)	(0.190)	(0.0056)
Observations	9,553,448	5,054,166	6,842,516	9,600,529
		AGE 35-44		
Control group from SINE	0.212***	-0.588***	-2.332***	-0.0498***
	(0.00804)	(0.0612)	(0.405)	(0.00802)
Observations	4,915,824	2,432,280	3,406,160	4,937,580
		AGE 45-54		
Control group from SINE	0.203***	-0.447***	-2.553***	-0.0466***
	(0.00871)	(0.0855)	(0.470)	(0.00842)
Observations	2,230,648	1,033,986	1,525,256	2,236,044
		AGE 55-64		
Control group from SINE	0.193***	-0.352***	-2.662***	-0.0428***
	(0.00983)	(0.0823)	(0.459)	(0.00839)
Observations	519,800	238,998	367,758	519,732

Standard errors in parentheses
*** p<0,01, ** p<0,05, * p<0,1

The results by race are presented in Table 9. SINE has similar qualititive impact on white and non-white workers. Nevertheless, results suggest that the negative impact of SINE impact on the next job tenure is greater for white applicants, which suggests that the negative effect of the program on the tenure of the next job is less important for non-white applicants. It is important to note that RAIS is an administrative database where employers classify the race of employees based subjective criteria, which can be particularly problematic in a country as diverse as Brazil. Paixão et al. (2012) and Camara (2015) present results showing discrepancies between RAIS, PNAD, and Census data on race. Differences are significant and RAIS presents a higher proportion of whites compared to PNAD and the Census.[28] Thus, results from Table 9 must be interpreted with caution.

[28] Paixão et al (2012) show that RAIS, in 2009, identifies 61.2% of the individuals as whites while PNAD identifies 54.7% of workers of the same color or race in PNAD and Camara (2015) shows that 2010 RAIS data identifies 60% of workers as white and the 2010 Census only identifies 53% of workers as white. Race in the RAIS data presents five categories (indigenous, white, dark, yellow, brown) and for Table 9 we divided the data into white and non-white.

Table 9
Effect of SINE Referrals
Race

	Employment	**Time until**	**Mean**	**Reemployment**
		WHITE		
Control group from SINE	0.217***	-1.628***	-2.616***	-0.0571***
	(0.00973)	(0.0676)	(0.332)	(0.00733)
Observations	7,177,584	3,512,602	5,144,050	7,267,650
		NON-WHITE		
Control group from SINE	0.216***	-1.561***	-1.975***	-0.0345***
	(0.0055)	(0.0594)	(0.236)	(0.00687)
Observations	7,977,452	4,023,050	5,749,038	8,093,815

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3. Subgroup Analysis (unemployment status)

Table 10 shows the results of the analysis of the effect of SINE referrals on UI beneficiaries vs. non-beneficiaries.[29] This analysis is relevant, because there is evidence that access to UI affects incentives to have a formal employment. Specifically, Carvalho and Narita (2016) find that Brazil's formal sector workers who have access to UI have the ability and incentives to induce their own resignation to some extent. Except for the reemployment wage, the impact of SINE on UI non-beneficiaries present greater magnitude when compared to the effects on beneficiaries: they have a higher probability of getting a job within three months of the referral, their reduction in reemployment time is much more drastic (1 month), and the reduction in tenure is smaller (by 56 days). On the other hand, the reduction in the reemployment wage is smaller for the group of unemployment beneficiaries. Thus, SINE's effectiveness for UI beneficiaries might be affected by higher reservation UI recipients.

[29] For this analysis we use the simplified PSM model, adding dummies for the number of UI payments that the worker still has to receive. The exact matching is made by region and number of entitled payments. Finally, we did not include in the group of non-beneficiaries who applied for UI and did not receive the benefit.

Table 10
Effect of SINE Referrals
Unemployment Insurance Recipients Vs Non-Recipients

	Employment within 3 months	**Time until employment (months)**	**Mean tenure (months)**	**Reemployment Wage (log)**
UI Beneficiaries	0.170***	-0.175*	-3.249***	-0.0275***
	(0.00761)	(0.102)	(0.532)	(0.00502)
Observations	1,818,280	925,066	1,254,068	1,827,527
UI Non-beneficiaries	0.195***	-1.071***	-1.390***	-0.0475***
	(0.0103)	(0.0711)	(0.113)	(0.00503)
Observations	8,674,544	4,342,790	6,550,280	8,722,134

Standard errors in parentheses
*** p<0,01, ** p<0,05, * p<0,1

The long-term unemployed is an especially vulnerable group of applicants, defined as people who have been unemployed for more than 12 months. Results for this group show little difference in the effect of referrals on employment within three months, whereas the effect is stronger for this group in terms of the time it takes to get a job, which is 0,5 months shorter, and the mean tenure of the next job, which is 2 months longer. Nevertheless, the negative impact on wage is more pronouced for long term unemployment.

Table 11
Effect of SINE Referrals
Long-Term Unemployed

	Employment within 3 months	**Time until employment (months)**	**Mean tenure (months)**	**Reemployment Wage (log)**
Control group from SINE	0.217***	-1.389***	-2.363***	-0.0621***
	(0.00642)	(0.0795)	(0.195)	(0.0102)
Observations	5,501,560	1,747,928	3,435,318	5,620,236

Standard errors in parentheses
*** p<0,01, ** p<0,05, * p<0,1

5.3 Subgroup Analysis (internet-based referrals)

Technology is changing the manner in which public services are provided. Digital channels for labor intermediation have been adopeted in many countries to contribute to the effectiveness and efficiency of the service. Nevertheless, to our knowledge, little empirical evidence is available on how mobile technologies impacts labor intermediation services and employment outcomes, with Dammert et al. (2015) as one exception. They designed an experiement to assess the causal impacts of mobile phone (digital) public labor market intermediation in Peru.

The analysis presented in this paper contributes to our knowledge about digital channels for labor intermediation and investigates how online and face-to-face systems of service provision differ with respect to their effectiveness in placing job-seekers in formal jobs and the quality of such placements. This is an important aspect for intermediation services in many developed and developing economies, as recently the focus of labor policies has been on investing in the development of online intermediation platforms as a means to increase coverage and reduce costs. Table 12 shows the results of the analysis. The first panel provides the effect of SINE online referrals, while the second panel shows the effect of SINE online referrals against the control group using face-to-face referrals.

The results show that online referrals increase the probalility of finding a job within three months of the referrals by 13.4 percentage points and have a negative impact for the worker, as it reduces mean tenure by 1.9 monts and reemployment wage by 4.9 percent. We perform an additional analysis comparing the effect of face-to-face referrals versus internet referrals on the same outcomes. The results show that in general face-to-face referrals are more effective. The probability of getting a job within three months is 3 percentage points lower if the referral is online, the time until employment after the referral is 0.48 months longer, the mean tenure is 0.4 months lower, and the reemployment wage is 1% higher. Thus, results suggest that online referrals are effective, but to a lesser extent than face-to-face service. These results are consistent with those reported by Pignatti (2016), who finds that the Colombian intermediation service is more effective when it is provided face-to-face rather than online, suggesting that the effects on formality come from a better labour market matching resulting from face-to-face services provided.

Table 12
Effect of SINE Internet Referrals

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment Wage (log)
Control group from SINE	0.134*** (0.0128)	0.0306 (0.157)	-1.993*** (0.155)	-0.0491*** (0.00518)
Observations	303,784	179,666	154,664	312,825
Control group from face-to-face referral	-0.0308*** (0.00664)	0.484*** (0.166)	-0.454** (0.186)	0.0103*** (0.00438)
Observations	182,948	118,982	105,380	189,998

Standard errors in parentheses
*** p<0,01, ** p<0,05, * p<0,1

6. Conclusion

This paper exploits the rich administrative records of the National Employment System (SINE) and Annual Social Information Report (RAIS) to provide the first impact evaluation of SINE interview referrals on four labor market outcomes: likelihood of re-employment, time to re-employment, job tenure, and wage.

Using data from January 2012 to December 2016, we estimate difference-in-difference regressions to measure SINE's impact on labor market outcomes, Overall, SINE referrals increase the likelihood of re-employment in the first three months following referral and decrease the time to re-employment. Being referred by SINE has greater effects for less skilled workers compared to more highly skilled workers.

Nevertheless, an interview referral by SINE can reduce the time of employment and salary, Stigmatization effects on program participants or the lack of capacity of the PES to attract high quality job vacancy postings to the system might be contributing to these results.

The results provide a better explanation of the functioning of SINE and can contribute to the design of a better labor market policy. The heterogeneity of SINE's impact according to different subgroups suggests that specific support to each group of customers might improve the effectiveness of labor intermediation services. The use of the technology in the process of job interview referrals via the web contributes to the placement of worker. A combination of services provided at a SINE office and remotely should be considered to increase cost-effectiveness of the SINE network. More research is needed to understand where and in what cases remote services perform better. Nevertheless, online services have a smaller impact when compared to the service provided at a SINE office; thus, there is room for technological improvements in the matching algorithm used for online services to reduce the gap between face-to-face and remote services.

APPENDIX

Appendix A: Descriptive Statistics

Table A1
Effectiveness (Placement Rates) - Only One Referral per Month

Year	Referrals	Placed Workers	% Effectiveness
2012	4,248,086	719,670	17%
2013	4,811,115	826,112	17%
2014	4,271,055	680,159	16%
2015	3,761,148	610,373	16%
2016	3,023,378	399,137	13%
Total	20,114,782	3,235,451	16%

Table A2
Referrals Placed by Workers Status

Year	Employed		Unemployed	
	Placed	% Effectiveness	Placed	% Effectiveness
2012	35,746	16%	695,431	12%
2013	39,264	17%	799,508	12%
2014	33,390	18%	653,215	12%
2015	31,589	20%	585,156	12%
2016	29,286	23%	373,231	10%

Appendix B: Matching Quality

Figure B1
Kernel Density January 2012
Control Group from SINE

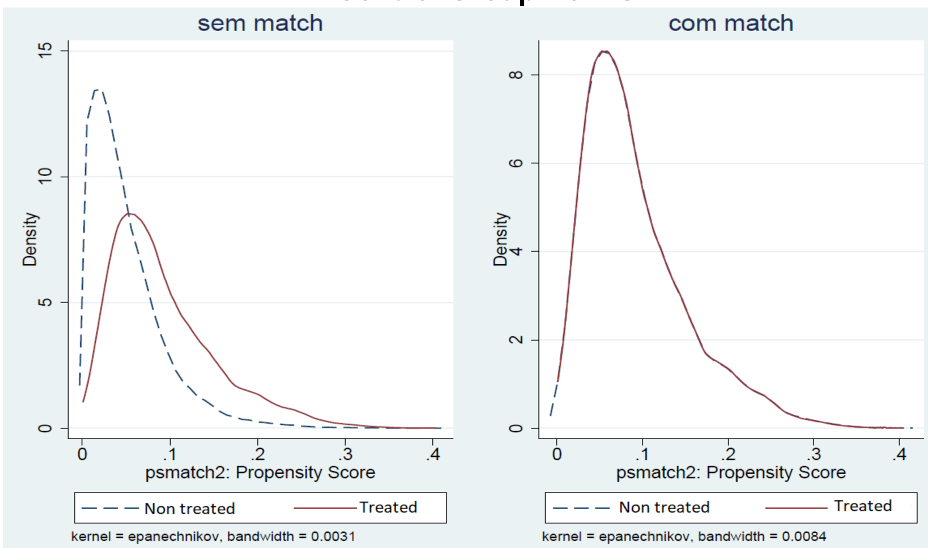


Figure B2
Kernel Density January 2012
Control Group from RAIS

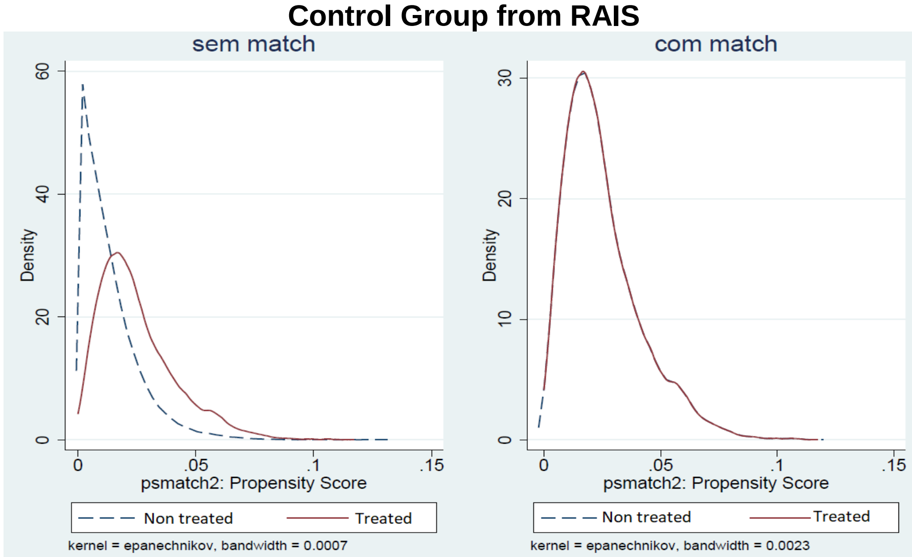


Figure B3
Rubin R test

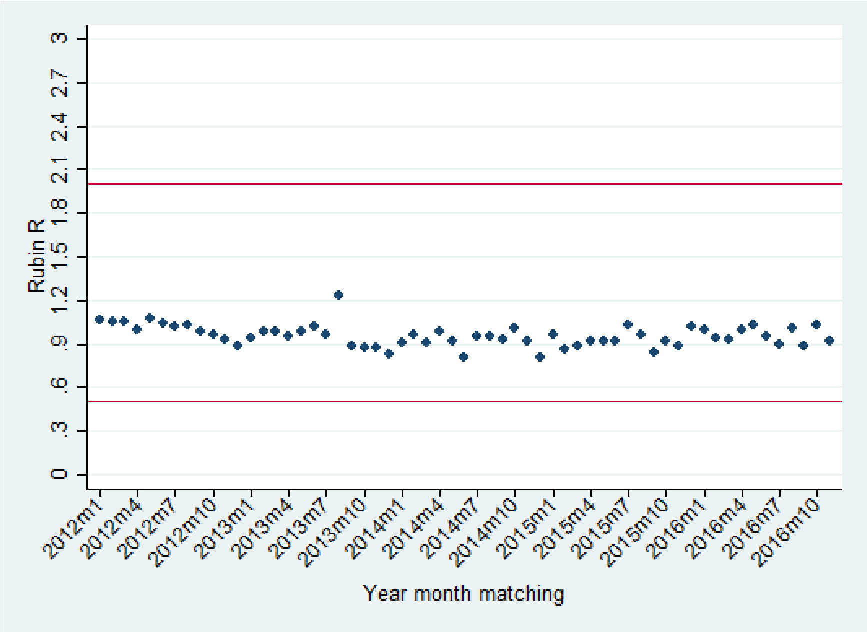
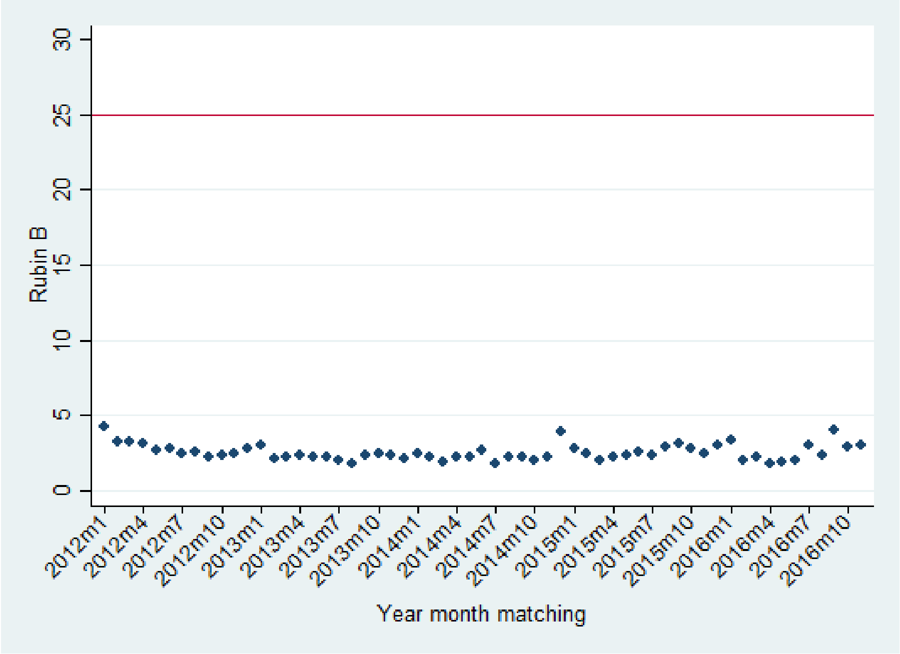


Figure B4
Rubin B Test



Appendix C: Results from RAIS Control Group

Table C5
Effect of SINE Referrals

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment Wage (log)
Control group from RAIS	0.215***	-1.489***	-1.801***	-0.0430***
	(0.00825)	(0.06930)	(0.11300)	(0.00749)
Observations	15,161,220	7,534,078	10,815,236	15,372,198

Standard errors in parentheses, *** p<0,01, ** p<0,05, * p<0,1

Table C6
Effect of SINE Referrals
Gender

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment Wage (log)
		MEN		
Control group from RAIS	0.228***	-1.322***	-1.914***	-0.0413***
	(0.00843)	(0.0720)	(0.1320)	(0.00868)
Observations	8,986,928	4,837,666	6,531,448	9,043,044
		WOMEN		
Control group from RAIS	0.205***	-1.626***	-2.017***	-0.0478***
	(0.0091)	(0.0653)	(0.0754)	(0.00601)
Observations	6,207,480	2,643,132	4,299,110	6,250,283

Standard errors in parentheses, *** p<0,01, ** p<0,05, * p<0,1

Table C7
Effect of SINE Referrals
Education

	Employment within 3 months	**Time until employment (months)**	**Mean tenure (months)**	**Reemployment Wage (log)**
		UNSKILLED		
Control group from RAIS	0.247***	-1.562***	-0.714**	-0.00991
	(0.0096)	(0.1270)	(0.2690)	(0.00643)
Observations	4,080,000	2,011,076	3,147,566	4,092,693
		SEMI-SKILLED		
Control group from RAIS	0.208***	-1.225***	-0.992***	-0.0418***
	(0.0088)	(0.0655)	(0.0870)	(0.00435)
Observations	20,231,620	9,839,618	14,386,546	20,366,826
		SKILLED		
Control group from RAIS	0.187***	-1.255***	-1.705***	-0.187***
	(0.0085)	(0.1100)	(0.1170)	(0.00816)
Observations	982,968	478,168	624,252	993,095

Standard errors in parentheses, *** p<0,01, ** p<0,05, * p<0,1

Table C8
Effect of SINE Referrals
Age

	Employment within 3 months	**Time until employment (months)**	**Mean tenure (months)**	**Reemployment Wage (log)**
		AGE 18-24		
Control group from RAIS	0.205***	-1.605***	-0.695***	-0.0450***
	(0.0105)	(0.0675)	(0.0418)	(0.00293)
Observations	7,933,968	3,704,468	5,951,694	7,995,836
		AGE 25-34		
Control group from RAIS	0.219***	-1.207***	-1.217***	-0.0476***
	(0.0080)	(0.0591)	(0.0854)	(0.00461)
Observations	9,553,616	5,087,732	6,832,434	6,606,847
		AGE 35-44		
Control group from RAIS	0.213***	-0.936***	-1.567***	-0.0424***
	(0.0083)	(0.0795)	(0.2420)	(0.00629)
Observations	4,915,880	2,429,986	3,396,862	4,944,908
		AGE 45-54		
Control group from RAIS	0.208***	-0.842***	-1.651***	-0.0404***
	(0.00923)	(0.08380)	(0.33900)	(0.00686)
Observations	2,230,752	1,024,086	1,519,686	2,240,483
		AGE 55-64		
Control group from RAIS	0.195***	-0.766***	-1.931***	-0.0328***
	(0.01070)	(0.12100)	(0.49800)	(0.00903)
Observations	519,900	237,228	365,850	521,157

Standard errors in parentheses
*** p<0,01, ** p<0,05, * p<0,1

Table C9
Effect of SINE Referrals
Race

	Employment within 3 months	**Time until employment (months)**	**Mean tenure (months)**	**Reemployment Wage (log)**
		WHITE		
Control group from RAIS	0.215***	-1.529***	-1.994***	-0.0536***
	(0.0114)	(0.0815)	(0.1180)	(0.00586)
Observations	7,179,748	3,509,444	5,102,088	7,271,616
		NON-WHITE		
Control group from RAIS	0.215***	-1.486***	-1.627***	-0.0327***
	(0.0063)	(0.0824)	(0.1010)	(0.0074)
Observations	7,980,572	4,020,452	5,710,792	8,099,307

Standard errors in parentheses
*** p<0,01, ** p<0,05, * p<0,1

Table C10
Effect of SINE Referrals
Long-Term Unemployed

	Employment within 3 months	**Time until employment (months)**	**Mean tenure (months)**	**Reemployment Wage (log)**
Control group from RAIS	0.219***	-1.166***	-2.241***	-0.0509***
	(0.0081)	(0.0886)	(0.1040)	(0.00863)
Observations	5,504,076	1,674,300	3,419,414	5,625,086

Standard errors in parentheses
*** p<0,01, ** p<0,05, * p<0,1

Table C11
Effect of SINE Internet Referrals

	Employment within 3 months	**Time until employment (months)**	**Mean tenure (months)**	**Reemployment Wage (log)**
Control group from RAIS	0.135***	0.0221	-2.083***	-0.0493***
	(0.0112)	(0.135)	(0.286)	(0.0049)
Observations	308,132	184,024	157,836	317,898

Standard errors in parentheses
*** p<0,01, ** p<0,05, * p<0,1

Appendix D: Mean Outcomes Post-Matching

Table D1
Mean Outcomes Post-Matching

Control Group from SINE	**Control**	**Treatment**
Employment within 3 months	0.39	0.59
Time until employment (months)	7.81	5.07
Mean tenure (months)	7.86	5.33
Reemployment Wage (log)	847.67	792.31

Appendix E – Effect of SINE for Referrals in 2012

Table E1
Effect of SINE for Referrals in 2012

	Employment within 3 months	**Time until employment (months)**	**Mean tenure (months)**	**Reemploymen t Wage (log)**
Control group from SINE	0.209*** (0.0129)	-2.399*** (0.159)	-3.857*** (0.155)	-0.0571*** (0.0087)
Observations	3,588,824	1,053,556	3,175,304	3,579,978

Standard errors in parentheses
*** p<0,01, ** p<0,05, * p<0,1

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