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The effect of job referrals on labor market outcomes in Brazil

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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 the online labor exchange is less effective than in-person services provided at SINE offices.

JEL Classification Codes: J18, J23, J68

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

Upjohn Institute working papers are meant to stimulate discussion and criticism among the policy research community. Content and opinions are the sole responsibility of the author.

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 percent in 2011–2014 to an average of 12 percent in the last four 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.

SINE focuses on less educated and low-skilled job seekers, but it 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 should inform policymakers about the effectiveness of SINE for the full range of customers. Improving 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 (nine weeks) to fill a skilled vacancy as compared to the LAC average (five weeks) (Aedo and Walker 2012).

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.

As a percentage of the total budget for all active labor market programs, spending on labor intermediation services in Brazil is low as compared to OECD countries. Brazil spends less than 2 percent of its active labor market program budgets on labor intermediation services delivered by SINE, whereas OECD countries spend an average of 10 percent of their active labor market program budgets on public labor exchanges (Silva, Almida, and Strokova 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.

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 job-seeker skills with employer job vacancies. Borges, Lobo, and Foguel (2017) estimate that PES labor intermediation in Brazil saved the Worker Protection Fund budget about R\$43 million in 2016 through reduced unemployment insurance (UI) payments. Because 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 PES, the paucity of research on program effectiveness in developing countries is remarkable. Among the studies conducted in the United States and Europe, the evidence is consistently positive (Johnson, Dickinson, and West 1985; Katz 1991; Jacobson

and Petta 2000; Blundell et al. 2004; O’Leary 2015; Warren and Klee 2017; Toohey 2017). Although 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. Whereas Flores Lima (2010) finds no significant effects of the PES on the probability of finding a job in Mexico, PES users almost doubled their earnings and tripled their 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.

Although 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 three 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. First, we provide a background of related literature and a description of the data and descriptive statistics used. We then present the methodology and results, followed by concluding remarks.

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, Dickinson, and West (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 methods of job seeking.

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 PES is achieved at the expense of job seekers who did not receive services, then displacement has occurred. However, displacement effects are unlikely to be a serious issue in cases where the PES facilitates a small percentage of labor market placements, as in Brazil, where only 3 percent of placements are made by SINE.

A European study by Launov and Wälde (2016) uses the Mortensen-Pissarides matching model and finds 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 a difference-in-differences (DID) approach 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, Crépon, and Gurgand (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.

Technology is changing the manner in which public services are provided. Digital channels for labor intermediation have been adopted in many countries to contribute to the effectiveness and efficiency of various services. Nevertheless, to our knowledge, little empirical evidence is available on how mobile technologies impact labor intermediation services and employment outcomes. An exception is Dammert, Galdo, and Galdo (2015), who designed an experiment 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 because the recent focus of labor policies has been on investing in the development of online intermediation platforms as a means to increase coverage and reduce costs.

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 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.

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 management of some components of the UI program, including payment of benefits.²

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. In addition, SINE's intermediation service involves the management of job

² See the following website for more details: <http://portalfat.mte.gov.br/programas-e-acoas-2/sistema-nacional-de-emprego-sine/>.

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), which allows us to track job seekers during the period of analysis.

SINE data are complemented by the RAIS annual administrative dataset, which is compiled by the Labor Ministry of Brazil and contains employment and earnings information on all formal firms and employed workers in a given year.³ All formally registered firms in Brazil report annual information on their employees. The RAIS dataset 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 the CPF.

For this study, we use RAIS data 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 allow us to observe workers with more than one job at the same time (i.e., multiple job holders). Because 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.⁴

³ 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.

⁴ 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.

Because most workers who seek SINE's assistance are unemployed (94 percent), 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.⁵

A person who received a referral in 2012 had a 90 percent probability of finding a formal job within the next five 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.⁶

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 allow 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 five-year available time span used in the paper is not short and that monthly analysis is required for short average job tenures.⁷

⁵ RAIS data include formal sector workers. We refer to non-employment in the formal sector as unemployment.

⁶ This is unlikely to be an issue even for the last year of the data; about 43% of workers who received a referral in 2016 got a job in the same year.

⁷ The average job tenure for the formal private sector in Brazil is about 3.5 years (DIEESE 2016).

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 as 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.⁸ While 70 percent of the vacancies⁹ available at SINE have at least one corresponding job interview referral, only 28 percent of the vacancies are filled through a SINE job referral. The overall placement rate (workers placed by referral) of SINE is about 12 percent throughout the period of analysis. Note that online self-service referrals were permitted starting in 2014.

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: Authors' calculation, based on data from the Ministry of Labor. Placement rate is the number of workers placed divided by the number of referrals.

To evaluate the impact of labor intermediation, we construct a monthly database with matches of referrals to non-referrals. The database matches only one referral each month per

⁸ Table 1 shows the number of new SINE registrants per year. For example, in 2016, 4,587,164 workers registered with SINE for the first time. Thus, 31.7 million is the number of unique workers registered.

⁹ 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.

individual, even if that individual was referred more than once in a month.¹⁰

Table 2 shows that 94 percent of the referrals are made for unemployed job seekers, which is the group of workers analyzed in this study.¹¹ The average age of the workers referred by SINE is about seven years higher for the unemployed than for the employed. The total mean age of all the SINE applicants is about 30 years old. Almost 50 percent of the workers are high school graduates, but only 11 percent have some college education. Finally, 58 percent of the registrants are male and 61 percent are considered non-white.

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 dropout/incomplete	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%

NOTE: The race categories are the standard groupings used by Brazilian national statistical agencies. Values for the variable in SINE data are assigned by SINE staff at the time of registration for services.

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

¹⁰ 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 that listed in Table 1 (see Table A.1).

¹¹ The relative number of matches is higher for employed job seekers, with a 19% placement rate as compared to a 12% rate for 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 employment status (Table A.2).

Brazil is well known for having wide regional variations culturally and economically, and this 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 most vacancies per registered job seeker (77.5 percent) and the most vacancies per employment office (16,720). However, the placement rate of the Paraná SINE offices is only 14.8 percent, 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 has a lower rate of vacancies per registered job seeker (35 percent) and the highest rate of job placements (46 percent), perhaps because its rate of referrals per office (4,316) is only one-tenth the rate in Paraná and the Federal District. Even though São Paulo, the richest and most populous state in the country, has the second most vacancies per labor intermediation office (13,998), it has a placement rate below the national average (7.2 percent). São Paulo had more than 10 million registered job seekers in the period, meaning each agency must serve more customers on average (31,889) as compared to other states, which leads to a modest rate of vacancies per job seeker (44 percent) 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	Offices	Vacancies	Vacancies per registered (%)	Registered workers per office	Vacancies per office	Referrals per office	Placements per office	Placement rate (%)
Acre	80,247	11	8,832	11.0	7,295	803	2,008	395	19.7
Alagoas	393,550	43	137,497	34.9	9,152	3,198	4,316	1,984	46.0
Amapá	83,460	12	12,673	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	563,919	30.3	12,479	3,785	9,216	1,962	21.3
Ceará	931,723	135	643,526	69.1	6,902	4,767	10,014	2,870	28.7
Dist Federal	501,929	26	233,878	46.6	19,305	8,995	41,793	2,492	6.0
Espírito Santo	642,186	34	185,039	28.8	18,888	5,442	11,152	792	7.1
Goiás	1,150,209	90	419,242	36.4	12,780	4,658	11,468	1,005	8.8
Maranhão	552,293	47	49,209	8.9	11,751	1,047	1,990	674	33.8
Mato Grosso	569,393	45	250,436	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	821,631	26.8	13,510	3,620	11,275	1,048	9.3
Pará	832,355	56	79,584	9.6	14,863	1,421	2,125	488	23.0
Paraíba	430,538	40	99,891	23.2	10,763	2,497	5,207	716	13.8
Paraná	1,878,055	87	1,454,639	77.5	21,587	16,720	44,362	6,583	14.8
Pernambuco	977,721	82	289,921	29.7	11,923	3,536	9,155	1,109	12.1
Piauí	307,818	31	33,474	10.9	9,930	1,080	1,843	254	13.8
Rio de Janeiro	2,362,499	127	1,013,274	42.9	18,602	7,979	8,708	922	10.6
Rio Gran do N	379,473	38	36,130	9.5	9,986	0,951	2,307	195	8.5
Rio Gran do S	1,791,515	128	662,611	37.0	13,996	5,177	14,273	1,519	10.6
Rondônia	234,515	20	52,050	22.2	11,726	2,603	6,221	921	14.8
Roraima	61,362	7	9,081	14.8	8,766	1,297	5,880	800	13.6
Santa Catarina	1,183,483	74	324,924	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	25,949	8.9	13,957	1,236	3,100	245	7.9
Tocantins	212,324	16	139,568	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.

METHODOLOGY

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 as compared to the labor market outcomes of 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, in practice, we cannot observe an outcome for service recipients as if they had not received it. To measure SINE's impact, therefore, 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 on those who were treated. The individuals in the matched comparison group are similar to the participants in observed characteristics, except for the referral. To this end, we construct a counterfactual for treated individuals 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:

$$(1) \quad P(D = 1|X) = \beta X + \gamma_1(Age + Job_{tenure} + \log(Wage) + Gender)D_{state} \\ + \gamma_2(Age + Job_{tenure} + \log(Wage) \\ + Gender)D_{month-year_{separation}} + \epsilon$$

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 (given in the next paragraph). 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.¹² Using these monthly samples of participants and non-participants, we estimate 60 PSM models. That is, we estimate one PSM model for each month in our panel, following the approach of Sianesi (2004). We use nearest-neighbor matching without replacement to create comparison groups. Individuals are matched with certainty on two characteristics: number of

¹² In other words, we count referrals and registrations in a given month only once.

months unemployed until matching and the workers' state of residence. Each treated individual is matched with a non-treated individual from the same state and who has the exact number of months unemployed until the matching.¹³

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 five categories: indigenous, white, dark, yellow, and brown), age in the year of the matching, gender, educational attainment (divided into 11 categories), and industrial sector (86 categories of CNAE¹⁴ at the 2-digit level) and occupational group (48 categories of CBO¹⁵ at the 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.¹⁶

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 because 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

¹³ Lechner (2002) also matches with a mixture of exact characteristics and propensity scores, matching exactly on gender, duration of unemployment, and native language. Lechner also uses propensity scores in an evaluation of active labor market programs in Switzerland.

¹⁴ CNAE is the national classification of economic activities.

¹⁵ CBO is the Brazilian classification of professions.

¹⁶ Heinrich, Maffioli, and Vázquez (2010) 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 [online self-referrals to job interviews], 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:

$$P(Y) = \beta X + \gamma(\text{Age} + \text{Job}_{\text{tenure}} + \log(\text{wage}) + \text{Gender} + \text{time}_{\text{until}_{\text{match}}})D_{\text{region}} + \epsilon$$

available in the RAIS at any point of our panel who were not referred for job interviews using SINE services (i.e., they did not visit a SINE office). These control groups are more subject to selection bias because most workers in RAIS do not visit a SINE office.¹⁷ 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 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. The matching is performed monthly, so the balance in the means of basic observable characteristics must be checked each month. Table 4 shows the *t*-test results for differences in means before and after matching for certain characteristics in November 2016. A bias reduction is expected after matching. The *t*-tests show that before matching, the participant and comparison groups are significantly 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.

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.¹⁸ The standardized bias of an estimated mean is the difference between the means of the participant and comparison groups divided by the average of the standard deviations for the two groups. If

¹⁷ 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 SINE, information from the RAIS was essential to calculate PSMs and measure the outcomes because it allowed us to track the employment history of each job seeker.

¹⁸ 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) were tested, and their results confirm the matching quality (see Figures B.3 and B.4).

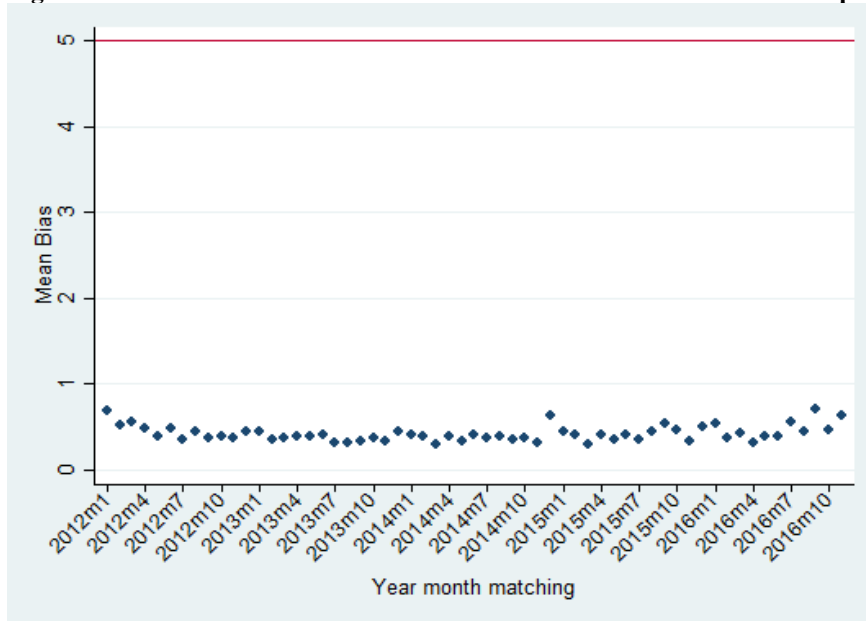
**Table 4 Descriptive Statistics Pre- and Post-Matching Treatment: Referrals
(Control Group: SINE November 2016)**

Variable	Sample	Mean		Bias (%)	Bias reduction (%)	<i>t</i>	<i>P> t </i>
		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.

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 percent after matching should be sufficient (Caliendo and Kopeinig 2008). Each point in Figure 1 represents the average of the standardized bias of the mean estimates averaged across all exogenous variables (used in the PSM) after matching, calculated for one month in the sample period. The figure shows that

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



matching was successful since the average bias is about half of a standard deviation across all monthly estimates.

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. The results are presented in Figures B.1 and B.2 in Appendix B, which show an overlap in the mean propensity scores and their distributions for the two groups after matching, suggesting that the PSM generates good matches.¹⁹

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 previously, to perform the matching, we restricted the database to workers who lost their job and obtained a new

¹⁹ 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.

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.

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 :

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

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 three months of the referral. In the evaluation, this variable is always 0 for the pre-matching period.²⁰ *Time until employment* is the unemployment time between jobs, calculated as the date of admission to the next job minus the date of separation from the previous job.²¹ *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. Finally, *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 1 after treatment. The variable *SINE* is the interaction between *Treated* and *Post*. θ , the

²⁰ To evaluate this outcome, we remove matches from September 2016 onwards to leave only observations that are well defined (individuals that possess at least 3 months of information for this outcome).

²¹ The sample of this database is especially restricted because it requires each worker to have at least three jobs in the panel to allow for unemployment time between jobs before and after the treatment.

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 represents the monthly dummy variables. The matrix X includes alternative education and sector variables for individual workers who are not included in the PSM.²² 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.²³

RESULTS

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 as compared to workers who were registered at SINE but did not get a job referral.²⁴

The treatment increases the likelihood of finding a job within three months of the referral by 19.7 percentage points (Table 5). In addition, job seekers who are referred by SINE take less time (0.9 months) to find a job, but SINE job referrals have a negative impact on the mean tenure of the next job found (a 4.1 month reduction). Finally, being treated by SINE reduces wages by about 3.5 percent,²⁵ which is consistent with Pignatti (2016) and Vera (2013) and might be related to stigmatization effects on SINE participants or the lack of the program's capacity to attract high-

²² Education is disaggregated into three categories: unskilled (from illiterate to completed primary school), semi-skilled (from some to completed high school), and skilled (from some undergraduate education to PhD). The sector of the last job from the IBGE Classification is aggregated in the following categories: agriculture, industry, services, trade, construction, and other.

²³ These variables are included in the difference-in-difference estimations, but they were not available when the PSMs were calculated. Difference-in-difference estimations without the variables included in vector X provide similar results.

²⁴ Results using RAIS for control groups are very similar and are provided in Appendix C.

²⁵ Appendix D provides an indication of the size of SINE's impact on outcomes. For example, 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 percentage points.

paying enterprises.²⁶ The estimated effects are the average for the period of analysis. Because of the short job tenure duration and high worker turnover in the Brazilian labor market, the five-year time span was sufficient to provide results on how SINE affects labor market outcomes.²⁷

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

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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.²⁸

Results disaggregated by gender are presented in Table 6. The positive and negative effects are in the same direction as the overall estimations provided in Table 5, but the impact of an interview referral is different for women and men. SINE increases the probability of finding a job within three months by 23 percentage points for men and 21 percentage points for women. The

²⁶ 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 are R\$140 lower than a similar firm that does not post vacancies at SINE. The results that SINE referrals decrease the time to reemployment but also reduce the time of employment and salary need further investigation because getting a job faster may be related to a poor quality of the matching. Nevertheless, the overall data do not provide a clear correlation between time until employment and tenure and salary.

²⁷ 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.

²⁸ The effects across groups are not compared directly to estimates on the full sample because the DID estimates and PSMs matches are done separately for each subgroup sample (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 by Gender

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

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

reemployment wage, however, is reduced by 4 percent for men and 5 percent for women, whereas the time until employment is reduced by 1.8 months for men and 1.4 months for women.

Understanding the heterogeneous impact of the labor intermediation across workers with different levels of education is important. Education is disaggregated into three categories in Table 7: unskilled (from illiterate to completed primary school), semi-skilled (some or completed high school), and skilled (from some undergraduate education to PhD). Most of the applicants (80 percent) are considered semi-skilled, and 10 percent each are considered unskilled and 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 getting a job for lower skilled applicants (compared to the same non-treated group) more effectively as compared to the group of skilled workers. Also, the wage-lowering effect of SINE referrals (compared to the non-referred) is stronger for the most skilled applicants (1 percent for unskilled job seekers versus a 22 percent drop for skilled workers). This negative effect on wages might signal SINE's inability to attract high-quality vacancies. Unskilled applicants referred by SINE also have the greatest reduction in time until employment (1.2 months) as compared to semi-skilled (1.0) and skilled (0.9) job seekers. In addition, SINE also reduces the job tenure of unskilled workers by the lowest amount (1.3 months) as compared with semi-skilled (1.6) and skilled (2.4) applicants with job referrals.

Table 7 Effect of SINE Referrals by Education

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment 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

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The size of the positive effect of SINE referrals on the time to find a job diminishes as workers age (Table 8). The time reduction as compared to the control group decreases from 1.5 months in the youngest group (18–24 years old) to 0.35 in the oldest group (55–64 years old). In contrast, the negative effect of the referrals on job duration is greatest in the older groups, up to 2.6 months for the 55–64-year-old group.

Table 8 Effect of SINE Referrals by Age

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

NOTE: 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 qualitative impact on white and non-white workers, but the results suggest that the negative impact of SINE on job tenure is greater for white applicants. This 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 (a national household survey), and Census data on race. The differences are significant, and RAIS presents a higher proportion of whites as compared to PNAD and the Census.²⁹ Thus, the results on race must be interpreted with caution.

Table 9 Effect of SINE Referrals by Race

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

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Unemployment Status

Table 10 shows the results of the analysis of the effect of SINE referrals on UI beneficiaries vs. non-beneficiaries.³⁰ This analysis is relevant because there is evidence that access to UI affects

²⁹ Paixão et al. (2012) show that RAIS, in 2009, identifies 61.2% of the individuals as whites, whereas PNAD identifies 54.7% of workers as white. 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 is divided into five categories in the RAIS data (indigenous, white, dark, yellow, and brown), but we divided the data into white and non-white in Table 9.

³⁰ 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 people who applied for UI and did not receive the benefit in the group of non-beneficiaries.

incentives to have 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 resignations to some extent. Except for the reemployment wage, the impact of SINE on UI non-beneficiaries is greater as 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 greater (by almost one 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.

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*** (0.00761)	-0.175* (0.102)	-3.249*** (0.532)	-0.0275*** (0.00502)
Observations	1,818,280	925,066	1,254,068	1,827,527
UI Non-beneficiaries	0.195*** (0.0103)	-1.071*** (0.0711)	-1.390*** (0.113)	-0.0475*** (0.00503)
Observations	8,674,544	4,342,790	6,550,280	8,722,134

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The long-term unemployed, defined as people who have been unemployed for more than 12 months, is an especially vulnerable group of applicants. 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 (Table 11). Nevertheless, the negative impact on wage is more pronounced 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*** (0.00642)	-1.389*** (0.0795)	-2.363*** (0.195)	-0.0621*** (0.0102)
Observations	5,501,560	1,747,928	3,435,318	5,620,236

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Internet-Based Referrals

Table 12 shows the results of the internet-referral analysis. The first panel provides the effect of SINE online referrals, and the second panel shows the effect of SINE online referrals against the control group using face-to-face referrals. Online referrals increase the probability of finding a job within three months of the referrals by 13.4 percentage points, but they reduce mean tenure by 1.9 months and the reemployment wage by 4.9 percent. The results show that face-to-face referrals are generally more effective. The probability of getting a job within three months is 3 percentage points lower with online referrals, 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 percent higher. Thus, the 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.

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 referrals	-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

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

CONCLUSION

This paper exploits the rich administrative records of SINE and RAIS to provide the first impact evaluation of SINE interview referrals on four labor market outcomes: likelihood of reemployment, time to reemployment, 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 reemployment in the first three months following referral and decrease the time to reemployment. Being referred by SINE has greater effects for less skilled workers as compared the effects on more highly skilled workers,

At the same time, 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 contribute 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 has mixed effects on worker placement. A combination of services provided at SINE offices and remotely should be considered to increase the cost-effectiveness of the network. More research is needed to understand where and in what cases remote services perform better because online services have a smaller impact as compared to in-person services provided at a SINE offices. Thus, there is room for technological improvements in the matching algorithms used for online services to reduce the gap between face-to-face and remote services.

APPENDIX A: DESCRIPTIVE STATISTICS

Table A.1 Placement Rate—Only One Referral per Month

Year	Referrals	Placed workers	Placement rate (%)
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 A.2 Referrals Placed by Workers Status

Year	Employed		Unemployed	
	Placed	Placement rate (%)	Placed	Placement rate (%)
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 B.1 Kernel Density January 2012—Control Group from SINE

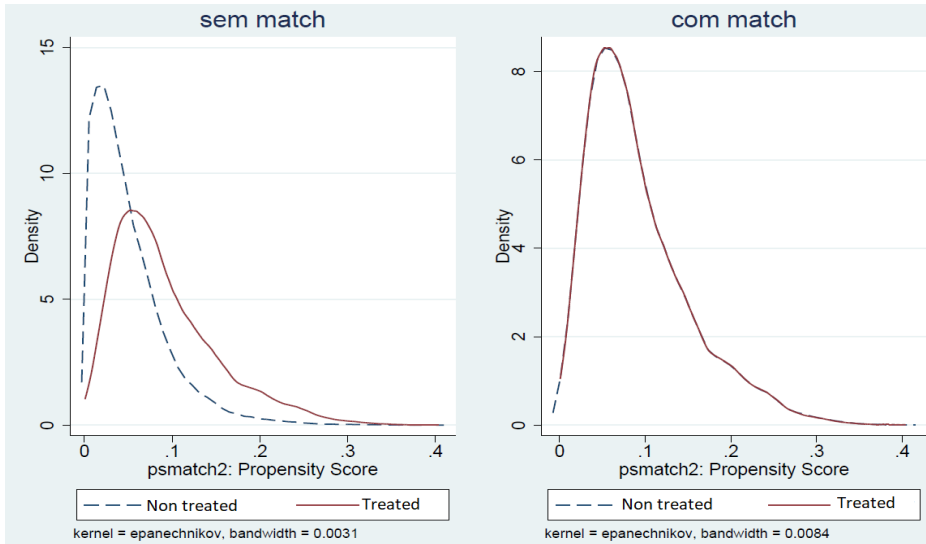


Figure B.2 Kernel Density January 2012—Control Group from RAIS

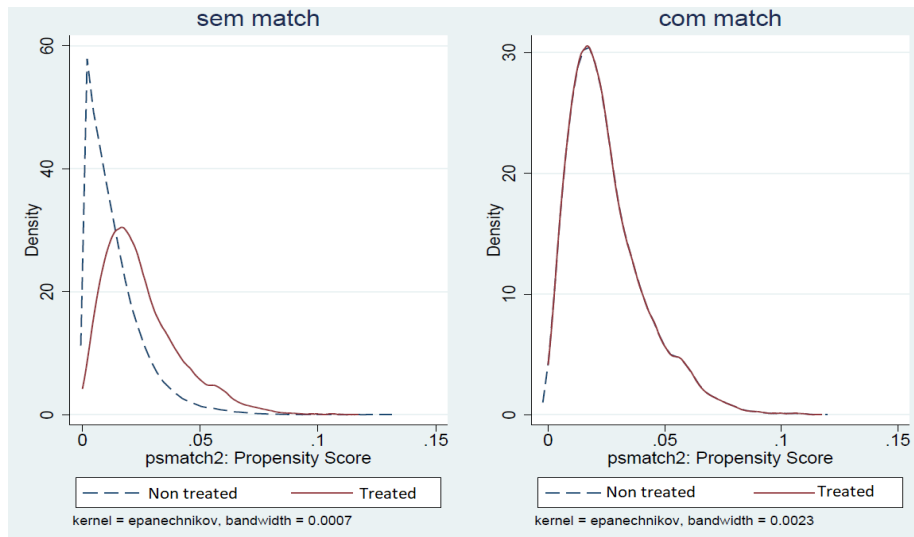


Figure B.3 Rubin R Test

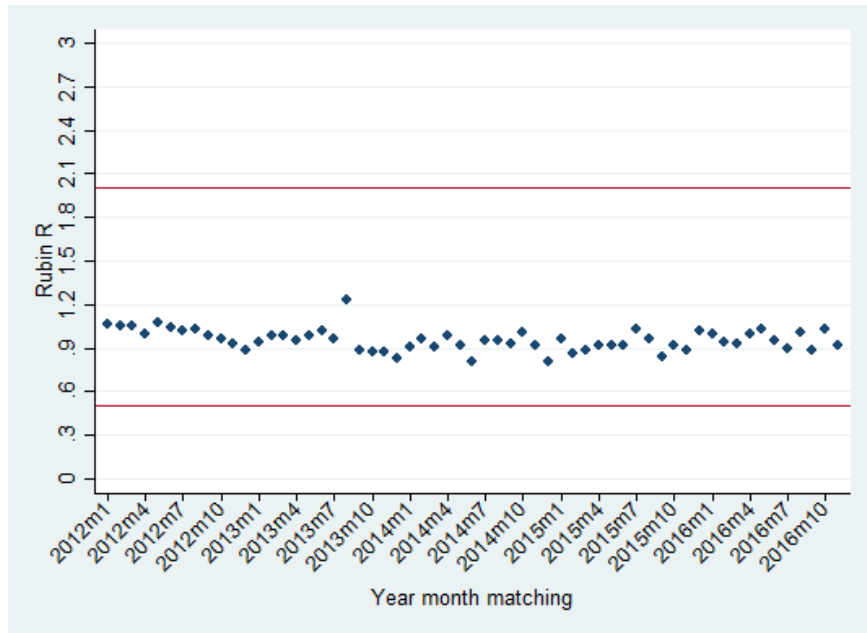
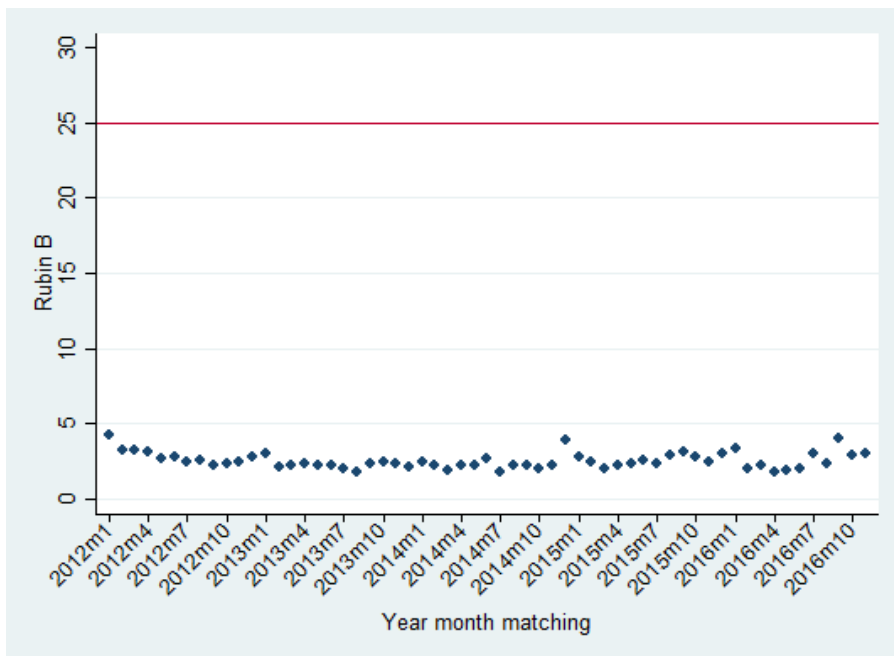


Figure B.4 Rubin B Test



APPENDIX C: RESULTS FROM THE RAIS CONTROL GROUP

Table C.1 Effect of SINE Referrals

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

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.2 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*** (0.00843)	-1.322*** (0.0720)	-1.914*** (0.1320)	-0.0413*** (0.00868)
Observations	8,986,928	4,837,666	6,531,448	9,043,044
Women				
Control group from RAIS	0.205*** (0.0091)	-1.626*** (0.0653)	-2.017*** (0.0754)	-0.0478*** (0.00601)
Observations	6,207,480	2,643,132	4,299,110	6,250,283

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.3 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*** (0.0096)	-1.562*** (0.1270)	-0.714** (0.2690)	-0.00991 (0.00643)
Observations	4,080,000	2,011,076	3,147,566	4,092,693
Semi-Skilled				
Control group from RAIS	0.208*** (0.0088)	-1.225*** (0.0655)	-0.992*** (0.0870)	-0.0418*** (0.00435)
Observations	20,231,620	9,839,618	14,386,546	20,366,826
Skilled				
Control group from RAIS	0.187*** (0.0085)	-1.255*** (0.1100)	-1.705*** (0.1170)	-0.187*** (0.00816)
Observations	982,968	478,168	624,252	993,095

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.5 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*** (0.0114)	-1.529*** (0.0815)	-1.994*** (0.1180)	-0.0536*** (0.00586)
Observations	7,179,748	3,509,444	5,102,088	7,271,616
Non-White				
Control group from RAIS	0.215*** (0.0063)	-1.486*** (0.0824)	-1.627*** (0.1010)	-0.0327*** (0.0074)
Observations	7,980,572	4,020,452	5,710,792	8,099,307

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.6 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*** (0.0081)	-1.166*** (0.0886)	-2.241*** (0.1040)	-0.0509*** (0.00863)
Observations	5,504,076	1,674,300	3,419,414	5,625,086

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.7 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*** (0.0112)	0.0221 (0.135)	-2.083*** (0.286)	-0.0493*** (0.0049)
Observations	308,132	184,024	157,836	317,898

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

APPENDIX D: MEAN OUTCOMES POST-MATCHING

Table D.1 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 E.1 Effect of SINE for Referrals in 2012

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment 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

NOTE: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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