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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.

Effects 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. We use data from a five-year period (2012–2016) to evaluate the impact of SINE job referrals on reemployment, time until reemployment, job tenure, and wage rates. Causal impact estimates based on propensity score matching 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 needed to find reemployment, the average job tenure of the next job, and the reemployment wage. Subgroup analysis suggests that SINE is particularly effective at helping less educated workers find work in a timely fashion. Finally, the evidence suggests that the self-service online labor exchange works less well than the in-person job interview referrals provided at SINE offices.

Key words: labor market policy, employment services, job interview referrals, difference-in-differences.

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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, as labor market policy has become an important macroeconomic policy instrument in the LAC region, labor market programs have garnered a bigger share of public resources in the region and have served more job seekers and employers (Ramos 2002).

In Brazil, labor markets have performed reasonably well over the past 15 years in terms of labor market participation and labor earnings growth. However, a recession that started in the second quarter of 2014 nearly doubled the unemployment rate, from an average of 6.9 percent in 2011–2014 to an average of 12 percent in the subsequent four years.[1] The country's National Employment System (SINE) is a key institution for public employment policies and can take a greater role in future economic downturns.

SINE, created in 1975, is a network of local employment offices. It serves as a go-between, helping workers line up work and providing information to employers on available workers.[2] The Worker Protection Fund, established in 1990, expanded SINE to 1,930 offices in 2016, with locations throughout the country in all 26 states and the federal district. The Ministry

[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 second quarter of 2014 to the last quarter of 2016.
[2] SINE was created as a result of ratification by the Brazilian government of the Convention No. 88 of the International Labor Organization (ILO), which relates to the organization of public employment services. SINE is also one of the means through which workers request unemployment benefits. For more details about SINE, see IPEA (2020) and Lobo and Anze (2016).

of Labor[3] coordinates this large network, monitoring the decentralized delivery of services by states and municipalities.

SINE customers tend to be less educated and lower skilled, but SINE also provides services for customers with higher educational attainment and job qualifications. In this paper, we estimate the program's causal impacts on the full range of customers and analyze the effects of job referrals on all customers, most of whom have work histories characterized by high rates of turnover in formal-sector jobs. Our estimates suggest that SINE job referrals increase the probability of finding a job and reduce the time to reemployment, the average tenure in the next job, and the reemployment wage. Our subgroup analysis further suggests that SINE could broaden its impact by expanding services to more highly trained job seekers. We find that it takes almost twice as long (nine weeks) to fill a skilled job vacancy in Brazil as it does on average (five weeks) in other LAC countries (Aedo and Walker 2012).

Improving the effectiveness of the public employment service (PES) is essential to supporting quick, successful, and high-quality job matches (Betcherman et al. 2004). An effective PES contributes to labor-market efficiency, reducing informational breakdowns that slow or prevent the proper matching of job-seekers' skills to employer job vacancies. Borges et al. (2017) estimate that PES labor intermediation in Brazil saved the Worker Protection Fund about R$43 million in 2016 through reduced unemployment insurance (UI) payments. Since labor intermediation programs typically benefit low-skilled workers, countries with a large proportion of these job seekers could benefit from increased investment in labor exchange services.

[3] The Ministry of Labor was integrated into the Ministry of Economy following the restructuring of the federal ministries in 2019. The Secretariat of Productivity, Employment, and Competitiveness in the Ministry of Labor is currently responsible for the SINE network.

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 on labor intermediation services, while OECD countries spend an average of 10 percent (Silva et al. 2015). Since the PES provides services free of charge, it also improves equity in access to social participation through the labor market. Although not an explicitly stated organizational objective, the movement of workers from informal to formal sector jobs by PES might provide access to private health insurance and other benefits. 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. The studies conducted in the United States and Europe consistently find evidence for public labor exchange services in those developed countries to be a positive (Johnson et al. 1985; Blundell et al. 2004; Michaelides and Mueser 2018). While the estimated impacts on employment and earnings are typically small, the low cost of interventions often makes PES job search assistance services cost effective.

The few studies from Latin American showing causal evidence from survey data contain mixed results. Vera (2013), based on a small survey of 150 job applicants, finds that participation in the PES in Peru lengthens unemployment spells by 33 days. Pignatti (2016), utilizing a nationwide survey for Colombia, finds that the Colombian PES increased participants’ likelihood of having a formal job by between 5 and 31 percentage points but had a small negative effect on hourly earnings, which declined between 2 and 5 percent.

While high-quality statistics on the administration of nationwide programs in labor intermediation in Brazil exist, to date there has not been a formal impact evaluation. This paper is the first study in Latin America to use a large body of data to produce a more robust evaluation of a labor intermediation service. Using administrative microdata from 2012 to 2016, our study combines propensity score matching with difference-in-difference estimators to assess the impact of SINE's job referral on labor market outcomes. These difference-in-difference estimations show that a job referral by SINE increases employment probability within the next three months and reduces the number of months until employment. However, we also find that SINE referrals decrease the average tenure and salary of the next job. Our paper shows two other things: 1) SINE's impact differs according to its use by different subgroups, and 2) web-based job interview referrals contribute to the placement of workers but are less effective than face-to-face services in shortening nonemployment spells. Such knowledge helps administrators design strategies to make labor intermediation services better.

The remainder of this paper is structured as follows. Section 2 provides a background on related literature. Section 3 gives a description of data and summary statistics. Section 4 details our methodology, and Section 5 presents results. Section 6 offers concluding remarks.

2. Background

Previous researchers give us mixed evidence on the effectiveness of work intermediation programs. Evaluations of the PES have focused mainly on the service's impacts on employment probability, unemployment duration, and earnings. Specifically, some papers attempt to estimate national average employment impacts. One of the earliest attempts to assess the impact of job interview referrals in the United States is provided by Johnson et al. (1985), who use observational data from program administrative records to evaluate the effect of referrals to job interviews made by local offices of the U.S. Employment Service (ES). They identify the program effect by matching on observable characteristics. A subsample of ES registrants not given a job referral was selected by matching on observable characteristics to those whom the ES had referred to job interviews. 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 compared to men in accessing other job finding methods. Matching on observables provides modest causal evidence.

A more recent study in the U.S. found positive effects from job interview referrals in randomized controlled trials (Michaelides and Mueser 2018). A field experiment in Nevada during the Great Recession randomly assigned to eligibility assessment and job search assistance UI applicants identified as likely to exhaust benefits. The job search assistance included skills assessment, resume preparation, job interview coaching, and interview referrals to employers with openings suited to the applicants' skills. The control group had to meet no requirements to continue receiving benefits. Strong causal evidence suggests the treatment group had a 15 percent lower rate of exhausting regular unemployment benefits and an average 7.0 and 8.2 percentage point higher reemployment rate one and two quarters after treatment assignment, respectively. The employment gain diminished but remained positive during six observable post-referral quarters.

In a European study, Blundell et al. (2004) use differences in the geographic rollout and demographic targeting of services to convincingly identify the effect of the New Deal for Young People, which formed the largest part of the New Deal, a workfare program introduced in the United Kingdom in 1998. The New Deal provided compulsory job search assistance to unemployment compensation applicants and wage subsidies to employers. The authors provide causal evidence 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 and diminished over time, perhaps because of displacement effects.

Crépon et al. (2013) use randomized controlled trials in a field experiment to measure the impacts of job placement assistance on the labor market outcomes of young, educated job seekers in France. They provide strong causal evidence to show that even though the program increases the likelihood of finding a stable job, the positive effect diminishes over time and often comes at the expense of other eligible workers. Crépon et al. suggest that French job placement assistance has little net effect on overall unemployment in the country. However, unlike the UK and French cases, the SINE in Brazil facilitates only about 3 percent of job placements, suggesting that displacement effects are a smaller concern.

A study by Launov and Wälde (2016) uses program changes to identify the impacts of the Hartz reforms in Germany, which dealt with unemployment benefits programs and job placement procedures. They estimate that the program changes reduced unemployment nationwide by 0.88 percentage points. Notably, these reforms 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 hard to serve. Changes in job placement methods had the biggest effect, as the authors estimate that employment-agency changes explain about 20 percent of the decline in unemployment, while unemployment benefit reductions explain only about 5 percent.

There are few studies evaluating the effectiveness of PES agencies in South America. Vera (2013) conducted one study in Peru using a quasi-experimental design. She finds that job search assistance provided by the Peruvian PES had only small impacts on unemployment spells compared to job search assistance from private agencies. Vera suggests that the weak effects of PES result from barriers such as the limited geographic coverage of PES offices, the large informal sector, low use of the PES by highly skilled persons, high job turnover, lack of unemployment benefits, and little confidence in public-sector institutions. However, her research design has important limitations for generating convincing causal evidence: the treated sample is based on information on the beneficiaries of the program collected from a survey distributed to only 150 job applicants whom the PES had placed in a job in September 2004.

Pignatti (2016) uses propensity score matching to identify causal effects of job placements by the Colombian PES compared to job placements by other means such as private agencies, public posting of job openings, newspaper or website advertisements, or family and friends. Using data from the annual household survey (Gran Encuesta Integrada de Hogares) conducted by the National Administrative Department for Statistics (Departamento Administrativo Nacional de Estadística) in 24 municipalities and all rural areas, the study finds evidence suggesting that using the Colombian PES positively impacts the probability of having a formal-sector job, since two-thirds of PES placements are in large companies. It further finds that PES placements reduce earnings; however, this overall result obscures the more detailed finding that earnings impacts are positive for low-skilled workers but negative for high-skilled workers. A limitation to the identification strategy is that Pignatti's (2016) 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 relies on 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. It 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 data set allows us to follow job seekers' labor history, both 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. In that study, Woltermann (2002) finds that the only significant channels for transition into formal-sector jobs were these three: 1) directly contacting the employer, 2) using connections through family and friends, and 3) 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 in Latin America does not provide a comprehensive impact evaluation of the effectiveness of labor intermediation programs on employment probability, earnings, time until reemployment, and job tenure. This paper constitutes the first attempt to understand the effectiveness of these nationwide labor market programs in the Latin American context, using data from Brazil.

3. Data and Descriptive Statistics

We constructed a unique data set, 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 worker-identification credentials, and managing some components of the UI program, including payment of benefits.[4]

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. The process of SINE labor intermediation begins with job search registration at a SINE office or online through the SINE website. Based on information in the SINE database, the labor exchange officer explores the possible job matches between the profiles of registered job seekers and listings of available jobs. The SINE job-matching expert then presents job interview opportunities to the job seeker that match his or her skills and experience profile and proceeds to offer any suitable job-interview referrals.[5] Since May 2014, the SINE job-interview referral system also allows job seekers to make an online self referral if the worker meets the minimum requirements listed by the employer in the job-vacancy posting.[6] Thus, the SINE labor

[4] See the following web page for more details: http://portalfat.mte.gov.br/programas-e-acoes-2/sistema-nacional-de-emprego-sine/.
[5] A worker that is a beneficiary of the unemployment-insurance benefit cannot refuse an interview referral without having an acceptable excuse (Federal Law No. 7.998 from 1990).
[6] In 2016, online self-referral accounted for 16 percent of the total number of referrals (see Table 1). The policy note by IPEA (2014) shows details of the flow chart of SINE's labor intermediation process.

intermediation process entails matching job-seeker profiles with the requirements of vacancies, referring workers to interviews based on the matching results, and capturing referral outcomes, which we use in this evaluation.

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 expire. The SINE database, used for the first time in the literature, contains socioeconomic information on workers taken from their registration forms (age, gender, education, and employment status), as well as information on 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 individual's unique identification number—*Cadastro de Pessoas Físicas* (CPF)—and allows us to track job seekers during the period of analysis.

The SINE data are complemented by RAIS annual administrative data compiled by the Labor Ministry of Brazil. These contain employment and earnings information on all formal firms and employed workers in a given year.[7] All formally registered firms in Brazil report annual information on their employees. The RAIS includes detailed information about the employer, the employee, and the employment relationship (wage, tenure, type of employment, hiring and separation dates, and reason for separation, among other facts). Importantly, RAIS is an employer-employee matched data set that can be linked to the SINE data set using CPF.

For this paper, the RAIS data were available from 2011 through 2016. The RAIS data set is structured so 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

[7] 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 percent of the formal sector.

each individual's employment status for that month. Our aim is to analyze the exit from unemployment (nonformal employment) of workers with past experience in formal-sector jobs.[8] The panel data allow us to observe workers with more than one job at the same time—i.e., multiple jobholders. Since job loss for a multiple jobholder does not result in full unemployment, our sample excludes workers who at some point had multiple simultaneous formal-sector jobs.[9]

Since most workers who seek SINE's assistance are unemployed (94 percent), we restrict the analysis to workers who were separated from their jobs at some point before a job interview referral. In the panel based on RAIS information, a period between jobs is a period of nonemployment in the formal sector. Using the separation and hiring dates in RAIS, we create a panel of individuals with formal employment histories and at least one nonemployment spell in the formal sector.[10]

Overall, the study addresses unemployed individuals who were never multiple jobholders in the period analyzed, but who had at least one job in the RAIS before a job interview referral. However, a job *after* the interview referral is used when the outcome requires this observation (e.g., reemployment wages, tenure in the next job).[11] The unemployment (or nonformal employment) periods correspond to the periods for individuals who were hired at some point during the time span of 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

[8] Outcomes are measured using RAIS records that only encompass formal workers.
[9] 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 state of formal employment.
[10] RAIS data include formal-sector workers. We refer to nonemployment in the formal sector as unemployment.
[11] We observe that a person who gets a referral in 2012 has a 90 percent probability of finding a formal job within the next five years. This means that for outcomes that require the observation of a job after the referral, restricting the panel to workers with at least one unemployment spell and a registry of formal employment after having been referred to a job interview by SINE retains most of the observations in our panel. For the last year of data, about 43 percent of workers who got referrals in 2016 got a job in that same year.

matching. In this data, we observe about 65,000 job interview referrals each month. The average job tenure is less than two years, suggesting that the available five-year time span for the data is sufficient, and that monthly analysis is necessary for analysis of job tenure.[12]

Combining the SINE and RAIS data sets 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 greatly from that time onward, according to the Ministry of Labor. Table 1 shows that the total number of unique workers registered in the SINE system reached 31.7 million for the 2012–2016 period.[13] While 70 percent of the vacancies[14] available at SINE have at least one 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.

[12] The average job tenure in this data is exactly 19.6 months. The average job tenure for the formal private sector in Brazil is about 3.5 years, according to the Inter-Union Department of Statistics and Socio-Economic Studies (DIEESE 2016).
[13] 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 did so. Thus, 31.7 million is the number of unique workers registered.
[14] 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" with at least one position filled. The data on vacancies, referrals, and workers placed are flows in each year.

Table 1 - Descriptive Statistics of SINE Labor Intermediation (2012-2016)

Year	Workers registered	Vacancies	Referrals	Workers placed	Placement rate (%)	Online referrals
2012	8,231,696	3,072,010	5,937,727	730,489	12	0
2013	7,480,241	3,597,192	6,745,416	838,320	12	0
2014	6,232,876	2,715,616	5,834,709	686,295	12	152,444
2015	5,185,316	1,758,888	4,900,375	616,497	13	243,167
2016	4,587,164	1,151,366	3,783,357	402,365	11	211,906
Total	**31,717,293**	**12,295,072**	**27,201,584**	**3,273,966**	**12**	**607,517**

NOTE: The placement rate is equal to the ratio of workers placed to referrals.
SOURCE: Authors' calculations based on data from the Ministry of Labor.

To evaluate the impact of labor intermediation, we construct a monthly database with matches of referrals to nonreferrals. The data match only one referral each month per individual, even if that individual was referred more than once in a month.[15]

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.[16] The average age of the workers referred by SINE is higher for the unemployed than for the employed, and the difference between the two groups is around seven years. The mean age of all SINE applicants is about 30 years old. While almost 50 percent of the workers are high school graduates, only 11 percent have some college education. Fifty-eight percent of the registrants are male, and 61 percent are considered nonwhite.

[15] The placement rate (workers placed by referral) that considers one referral per month is higher (16 percent) because the number of workers placed remains the same but the number of referrals is lower than listed in Table 1 (see Appendix A, Table A1).
[16] The relative number of matches is higher for employed job seekers, with 19 percent effectiveness, compared to 12 percent of placed workers on referrals made for the unemployed. This means that the chances of one getting a job might depend not only on the skills of job seekers, but also on 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 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

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

Brazil is well known for having wide regional variation in cultural and economic matters, and these disparities extend to the SINE system. Therefore, in estimating program effects, it is important to control for differences across states. Table 3 summarizes regional differences across Brazilian states when it comes to the provision of services in SINE offices. The state of Paraná lists the most referrals per employment office (44,362) and the most placements per office (6,583). However, the placement rate of job seekers in Paraná is only 14.8 percent, since it has a high number of job seekers per office. In contrast, Alagoas, with a lower number of referrals per office (4,316), has the highest rate of job placements (46.0 percent). Even though São Paulo is the richest and most populous state in the country, 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, but with 315 offices, it had only a moderately high number of job referrals per office (27,270). These heterogeneities suggest that unmeasured differences across states should be considered in the process of estimating the impacts of SINE services.

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

State	Workers registered (000s)	Offices per state	Vacancies	Referrals per office (1,000s)	Placements per office (1,000s)	Placement rate (%)
Acre	80,247	11	8,832	2.008	0.395	19.7
Alagoas	393,550	43	137,497	4.316	1.984	46.0
Amapá	83,460	12	12,673	1.461	0.118	8.1
Amazonas	453,945	29	140,717	5.074	1.428	28.1
Bahia	1,859,443	149	563,919	9.216	1.962	21.3
Ceará	931,723	135	643,526	10.014	2.870	28.7
Dist Federal	501,929	26	233,878	41.793	2.492	6.0
Espírito Santo	642,186	34	185,039	11.152	0.792	7.1
Goiás	1,150,209	90	419,242	11.468	1.005	8.8
Maranhão	552,293	47	49,209	1.990	0.674	33.8
Mato Grosso	569,393	45	250,436	10.416	2.067	19.8
Mato Gr do S	442,099	40	198,142	14.060	2.060	14.7
Minas Gerais	3,066,879	227	821,631	11.275	1.048	9.3
Pará	832,355	56	79,584	2.125	0.488	23.0
Paraíba	430,538	40	99,891	5.207	0.716	13.8
Paraná	1,878,055	87	1,454,639	44.362	6.583	14.8
Pernambuco	977,721	82	289,921	9.155	1.109	12.1
Piauí	307,818	31	33,474	1.843	0.254	13.8
Rio de Janeiro	2,362,499	127	1,013,274	8.708	0.922	10.6
Rio Gran do N	379,473	38	36,130	2.307	0.195	8.5
Rio Gran do S	1,791,515	128	662,611	14.273	1.519	10.6
Rondônia	234,515	20	52050	6.221	0.921	14.8
Roraima	61,362	7	9,081	5.880	0.800	13.6
Santa Catarina	1,183,483	74	324,924	9.947	1.026	10.3
São Paulo	10,045,183	315	4,409,235	27.270	1.970	7.2
Sergipe	293,09	21	25,949	3.100	0.245	7.9
Tocantins	212,324	16	139,568	22.394	4.002	17.9
Total	**31,717,287**	**1,930**	**12,295,072**	**14.098**	**1.697**	**12.0**

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

4. Methodology

4.1 The evaluation

The purpose of this paper, as we have stated, 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 the labor market outcomes of participants compared to nonparticipants. However, simple differences of means between participants and nonparticipants will not yield reliable estimates of program effects because the characteristics of the two groups are likely to be different, owing 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. SINE services match workers to vacancies based on a list of criteria, and this automated process might be more efficient than workers trying to find a job match by themselves.[17] However, we do not observe the outcome for service recipients had they *not* received the service. In this study, we use propensity score matching (PSM) to construct a counterfactual for the treated by selecting a group of nonparticipants who have a similar pretreatment conditional probability of receiving a treatment and then estimate group mean effects, or the average treatment effect on the treated. The individuals in the matched comparison group will be similar to the participants in observed characteristics, except for the referral. Application of PSM requires satisfaction of the conditional independence and common support assumptions.[18]

[17] The matching algorithm is based on occupation (up to seven occupations can be listed using the CBO, the Brazilian classification of professions), educational attainment, work, language skills, availability for traveling or staying away from home for long periods of time, and possession of a driver's license.
[18] The assumption of conditional independence (selection on observables) requires that, conditionally on a set of observed attributes, the distribution of the (counterfactual) nontreatment outcome in the treated group is the same as

The propensity scores used to balance characteristics between participant and nonparticipant groups are estimated by the following probit model for each group evaluated:

$$P(D=1|X)=\phi(\beta X+\gamma(Age+Job_{tenure}+log(wage)+Gender+ unemployent\_spell)D_{region}\,. \qquad (1)$$

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, and job interview referrals are measured on a year-month reference basis.[19] Using these monthly samples of participants and nonparticipants, we estimate 60 PSM models. That is, we estimate separate PSM models on each monthly data set of treated workers in our panel.[20] We follow the approach of Sianesi (2004), who estimates separate PSM models for each month in her panel data.[21] We use nearest-neighbor matching within the same state without replacement to create comparison groups.[22]

the (observed) distribution of the nontreatment outcome in the nontreated group. The common support assumption requires that all treated individuals have a counterpart in the nontreated population. This means that values of *X* in Equation (1) are related to similar propensity scores in the treatment and control groups. For details, see Blundell et al. (2004) and Heinrich et al. (2010).

[19] In other words, we count referrals and registrations in a given month only once. Workers who successfully get reemployed are removed from the sample.

[20] For each subgroup analysis performed in Section 5, 60 PSM models were estimated.

[21] Sianesi (2004) evaluated employment services in Sweden and developed this monthly subsample approach, because nearly every customer of the employment service gets at least one service at some point. Constructing monthly samples allows for program participants and nonparticipants in each month. Other job referrals in the same month or later months—or other services in later months—could be confounding factors in our evaluation design. Therefore, we assume that the distribution of receiving subsequent employment and training services is balanced between referrals and comparison group members.

[22] The use of the closest match minimizes the bias, as we guarantee the use of the most similar observation to construct the counterfactual (Heinrich et al. 2010). In other words, the match uses the closest propensity score to match one worker in the treatment group to a worker in the comparison group. We used the nearest matching without replacement, meaning workers in the control group are used only once as a match. Matching without replacement performs well when many comparison units overlap with the treatment group (Dehejia and Wahba 2002). There is a large availability of observations in the control group, and Appendix B shows that treatment and control groups overlap. Thus, matching without replacement is appropriate in our setting.

The term ϕ is the normal cumulative distribution function. The remaining observable individual characteristics in the vector X for the PSM are as follows: tenure of the last job before referral (in terms of 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), industrial sector (86 categories of CNAE[23] at the two-digit level) and occupational group (48 categories of CBOat the two-digit-level) in the person's last job, and number of months unemployed.[24] In addition, as shown in Equation (1), age, job tenure, wage, gender, and unemployment duration are interacted with region dummies.[25] Tenure on the last job before referral (months) and the logarithm of the average monthly salary on the last job were included in the PSM to reduce selection on unobservables, as these variables encompass information on unobservables (Heinrich et al. 2010).

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 in a given month. This approach mitigates selection bias on unobservables, since workers who visit a SINE office might have self-selected and received a job interview referral due to unobservable characteristics, such as their 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

[23] CNAE is the national classification of economic activities.
[24] As the large number of observations allows, we also estimated an alternative PSM whereby individuals are matched with certainty on two characteristics: 1) number of months unemployed until matching and 2) the workers' state of residence. Thus, each treated individual is matched with a nontreated individual from the same state—someone who also has the exact number of months unemployed until matching. These additional results are available upon request. The strategy of matching on exact characteristics is used by Lechner (2002), who performs matching using propensity scores and matching exactly on sex, duration of unemployment, and native language.
[25] Heinrich et al. (2010) suggest that interacting vector *X* with regions improves the matching model.

who were not referred for job interviews using SINE services. These control groups are more subject to selection bias, as most workers who are in RAIS do not visit a SINE office.[26] Thus, our main results, presented in the body of this paper, are based on the control groups applying the first strategy. Additionally, we require the common support condition to be met exactly. Our results for the alternate control groups are presented in Appendix A.

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 characteristics 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 matching is expected. The *t*-tests show that before matching, the participant and comparison groups are sigificantly different on most observable characteristics, but that after matching there are fewer significant differences. This suggests that the participant and nonparticipant matched samples are well balanced.

[26] 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. nonreferred 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 – Selected Descriptive Statistics Pre- and Post-Matching
Treatment Group: Referrals | Control Group: SINE, January 2016

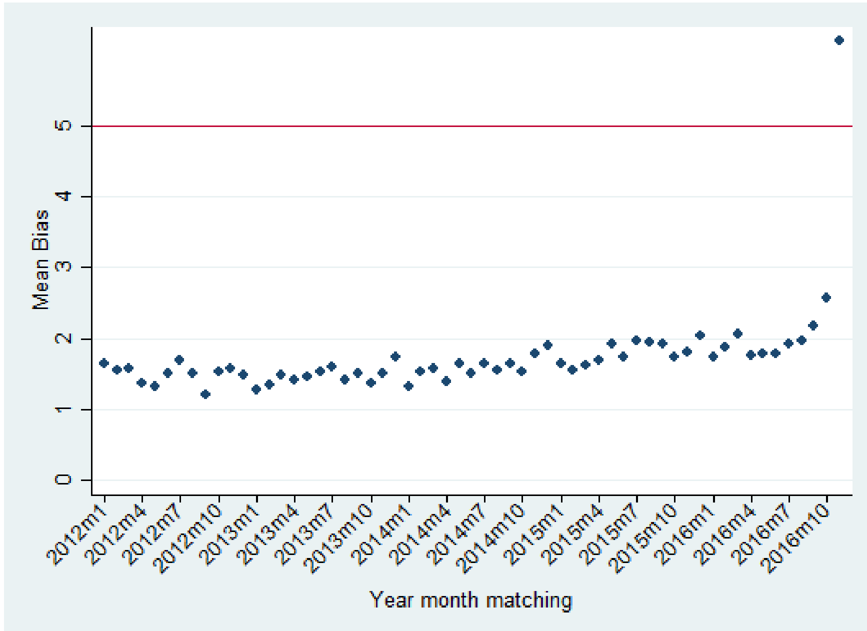
Variable	Sample	Mean		% bias	% bias reduction	*t*-test	P>|*t*|
		Treated	Control				
Male	Unmatched	0.549	0.583	7.05		20.064	0.00
	Matched	0.584	0.580	0.64	90.89	1.461	0.14
Age	Unmatched	31.474	32.831	12.58		36.922	0.00
	Matched	32.864	32.862	−0.27	97.78	−0.635	0.53
Tenure last job	Unmatched	24.073	15.594	−28.23		−94.025	0.00
	Matched	15.554	15.842	−1.126	96.00	−2.564	0.01
Mean wage last job (ln)	Unmatched	7.102	7.141	8.238		25.526	0.00
	Matched	7.143	7.144	−0.666	91.90	−1.517	0.13
White	Unmatched	0.445	0.460	2.914		8.263	0.00
	Matched	0.459	0.461	−0.151	94.81	−0.343	0.73
Elementary incomplete	Unmatched	0.029	0.031	1.518		4.260	0.00
	Matched	0.032	0.030	0.834	45.01	1.899	0.06
Elementary complete	Unmatched	0.031	0.030	−0.366		−1.042	0.30
	Matched	0.030	0.030	−0.347	−0.79	−0.790	0.43
Middle incomplete	Unmatched	0.081	0.085	1.550		4.371	0.00
	Matched	0.085	0.084	0.020	98.66	0.047	0.96
Middle complete	Unmatched	0.133	0.135	0.511		1.449	0.15
	Matched	0.135	0.151	−4.646	−808.64	−10.575	0.00
High school incomplete	Unmatched	0.165	0.126	−11.152		−32.558	0.00
	Matched	0.126	0.152	−7.481	32.68	−17.026	0.00
High school complete	Unmatched	0.478	0.542	12.467		35.405	0.00
	Matched	0.540	0.499	8.433	32.35	19.192	0.00
College incomplete	Unmatched	0.026	0.022	−2.659		−7.721	0.00
	Matched	0.022	0.017	3.591	−35.07	8.173	0.00
College complete	Unmatched	0.048	0.023	−13.518		−42.486	0.00
	Matched	0.023	0.027	−2.541	81.19	−5.784	0.00

SOURCE: Authors' calculations 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. 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 percent after matching should be sufficient (Caliendo and Kopeinig 2008). The dots in Figure 1 represents the value of the mean standardized bias calculated separately for each of the 60 months. In this case, the bias maintains an average value of 1.7 after the matching, an indication of the good quality of the PSM.[27] 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 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.[28]

[27] We also use the Rubin ratio test (see Rubin 2001), and the results confirm the quality of the matching, as the ratio of variances of the propensity score and covariates from the treatment and comparison groups is close to 1.0, and it is between 0.5 and 2.0 for each of the 60 months (see Figure B3 in the appendix).
[28] 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.

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



NOTE: For the five years of data, 60 monthly propensity-score matched pair samples were constructed. We computed the mean standardized bias between each monthly pair of participant and comparison group samples based on outcomes measured in the following month. Therefore, Figure 1 graphically displays 59 mean standardized bias estimates.

SOURCE: Authors' calculations.

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 had lost their jobs prior to SINE job referral, which allowed 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 difference-in-difference specification to estimate the impact of a job interview referral on labor market outcomes for worker *i*:

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

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 had gotten a job within three months of the referral. In the evaluation, this variable is always 0 for the pre-matching period.[29] *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.[30] *Mean tenure* is the tenure in the next job, and *reemployment wage* is the natural logarithm of real wages after the matching, compared to the last job before the matching.[31]

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*, whereas 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

[29] To evaluate this outcome, we remove matches from September 2016 onward in order to leave only observations that are well defined (individuals who possess at least three months of information for this outcome).
[30] Unemployment (nonformal employment) is calculated as the time between two jobs prior to the treatment. The calculation of the outcome time until employment requires information on two jobs prior to the job referral, generating a smaller number of observations for the regressions for this outcome. No further restrictions are imposed.
[31] The data for mean tenure and reemployment wages requires the observation of one job prior to and after matching to measure the outcomes; no further restrictions are imposed. As opposed to the method used for the calculation of the time until employment, the information on job tenure is observed in the record of employment prior to matching and does not need to be constructed from observing two jobs prior to the matching.

workers who are not included in the PSM.[32] 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.[33]

5. Results

5.1 Overall Results

The analysis seeks to measure the effect of referrals on the probability of workers' finding a job within three months of the referral. It also looks at time until employment, the mean tenure of the next job, and the reemployment salary, comparing these outcomes to those of workers who were registered at SINE but did not get a job referral.[34]

The results in Table 5 show that the treatment increases the likelihood of finding a job within three months of the referral by 20.0 percentage points. The probability of the control-group participants finding a job within three months is 24 percent; thus, a SINE interview referral nearly doubles their probability of finding a job within that time.[35] In addition, job seekers who are referred by SINE take less time (0.5 months less) to find a job than those who are not referred. This represents about a 6 percent reduction in the waiting time until they are able to secure a job, as in the control group the wait time is 8.00 months on average. However, SINE job referrals have a negative impact on the mean tenure of the next job found. On average, job tenure is reduced by 3.5 months, which equates to a 18 percent reduction in the average job

[32] Education is disaggregated into three categories: 1) unskilled (from illiterate to completed primary school), 2) semiskilled (incomplete and completed high school), and 3) skilled (from incomplete 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.
[33] These variables are included in the difference-in-difference estimations, as they were not available when the main bulk of PSM was calculated. Alternative estimations including these variables in the PSM or difference-in-difference estimations, without the variables included in vector *X*, provide similar results.
[34] Results using RAIS for control groups are very similar and are provided in Appendix C.
[35] Appendix D provides an indication on the size of SINE's impact on outcomes. For instance, 0.24 percent of workers in the control group obtained a job within three months after matching, and SINE increased this probability by 0.20 percentage points.

tenure of 19.6 months found in the data.[36] Finally, being treated by SINE reduces wages by about 5.8 percent. This result is consistent with Pignatti (2016) and Vera (2013) and may be related to stigmatization effects on SINE participants or the lack of capacity in the program to attract high-paying enterprises to the system.[37] The estimated effects are the average for the period of analysis, and because of the short job-tenure duration and high worker turnover in the Brazilian labor market, the five-year time span is sufficient to provide results about how SINE affects labor market outcomes.[38] Subgroup analysis based on workers' characteristics is provided in the next section.

Table 5 — Effect of SINE Referrals

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment wge (log)
Effect from SINE (relative to control)	0.200*** (0.0102)	−0.452** (0.173)	−3.533*** (0.233)	−0.0580*** (0.00605)
Observations	20,359,236	9,233,184	14,738,524	14,699,527

NOTE: Standard errors in parentheses. * = p < 0.10; ** = p < 0.05; *** = p < 0.01.
SOURCE: Authors' calculations.

5.2 Demographic Subgroup Analyses

Subgroup estimates reveal differences in the impacts of SINE services across groups of customers. These estimates help shape the strategy for providing services to workers with

[36] See footnote 13.

[37] We used PSM to match firms that posted vacancies at SINE in 2015 and firms that did not. 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 a firm that posts vacancies at SINE are 140 Brazilian reais lower than wages at a similar firm that does not post vacancies at SINE. Other results indicating that SINE referrals decrease the time to reemployment but also reduce salary and time of employment need further investigation, as getting a job faster may be related to a worse quality of matching. Nevertheless, the overall data do not provide a clear correlation between time until employment and tenure/salary.

[38] Appendix E, Table E1, provides separate estimates for each year. Results are similar for the initial years of the panel, when there is a longer time span for the outcomes to materialize in. Results for the latter years of the sample, particularly for 2016, go in the same direction but are biased, as they are influenced by a shorter time span in which to observe reemployment and the effects of SINE job referral.

different characteristics. Our methodology for estimating subgroup impacts involves estimating separate PSM for each subgroup category in each of the 60 months, using these to create matched-pair comparison groups for each subgroup category, then estimating the effects of job referrals by DID for each subgroup category.[39] Procedures for constructing samples to measure each of the four outcomes follow the same steps as listed in the methodology section. Impact estimates for subgroups defined by characteristics of age, sex, race, and educational attainment are presented in Table 6.

The general pattern of effect estimates on outcomes for each subgroup is similar to the full sample pattern of impact estimates presented in Table 5: that is, an increased percentage employed within three months of job interview referral, fewer months until reemployment, fewer months of job tenure in the new job, and lower reemployment earnings. However, there are some significant differences in impact estimates between some subgroup categories.

By age group, the size of the positive effects of SINE referrals on the time to find a job are smallest for the youngest (18–24). Indeed, the youngest group has a significantly smaller positive effect than all age groups.[40] The effect on shortening the time until reemployment is significantly greater for the oldest (55–64) group and significantly smaller for the prime age groups (25–34; 35–44), with no significant differences in effects between the age groups of 25–

[39] The effects across groups and overall effects are not directly compared, as the DID estimations and PSMs are conducted separately for each subgroup (e.g., comparing women who get interview referrals to women who do 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 estimations of 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 across different 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.

[40] The results for the age group between 55 and 64 is influenced by retirement, as Brazil's average retirement ages is 56 years for men and 53 years for women. A minimum number of years of contribution to the system provided eligibility for pensions, irrespective of age, because of legislation in place during the period analyzed in this paper (OECD 2017). See https://www.oecd.org/brazil/reforming-brazil-pension-system-april-2017-oecd-policy-memo.pdf.

34, 35–44, and 45–54. The effects on decreasing tenure in the new job grow steadily larger with age. These effects are significantly different between each of the five age groups: the smallest effect of 2.76 fewer months occurs in the youngest age group (18–24), and the largest effect of 6.95 fewer months occurs in the oldest age group (55–64). Job referrals reduced reemployment wages the most for the younger prime-age workers (25–34), at a rate of 5.9 percent. This reduction is significantly larger than for the youngest workers (18–24), who had a rate of 4.1 percent. Reemployment earnings reductions for the three older age groups declined with age, falling from 5.6 percent (35–44) to 5.2 percent (45–54), to 5.0 percent (55–64).

By gender, the impact of a SINE job interview referral had significantly better effects for men than for women on the probability of finding a job. For men, the increase in the probability of reemployment within three months is larger—27 percentage points, compared to 24 percentage points for women. On the other hand, SINE reduces women's time until employment by 3.8 months, as opposed to 3.1 months for men. There were no appreciable differences between the genders in the reduction in reemployment job tenure or the reduction in reemployment earnings.

Considering differences in impacts by race, SINE job referrals had generally better impacts for nonwhites than for whites. There was no difference by race in the impact on the probability of employment within three months, although the time to reemployment was reduced more for whites than for nonwhites. However, the reduction in new job tenure was bigger for whites, as was the reduction in reemployment wages. RAIS is an administrative database in which employers classify the race of employees based on subjective criteria. This can be particularly problematic in a country as diverse as Brazil. Paixão et al. (2012) and Câmara (2015) present results showing discrepancies between RAIS, PNAD, and census data on race. The differences are significant, as RAIS presents a higher proportion of whites than PNAD and the census.[41] Using RAIS data, Cornwell et al. (2017) show that when a worker changes jobs, the new employer might report a different race than the previous employer, and differences in race reporting are systematically associated with variation in wages. Thus, our results by race must be interpreted with caution.

Most workers (90 percent) who seek SINE's support have at least completed secondary education. While there is self-selection in the level of educational attainment, simple subgroup differences in impacts on employment outcomes by educational attainment help to inform decisions on program refinement. We grouped educational attainment into three categories: 1) unskilled (from illiterate to completing primary school), 2) semiskilled (some high school attendance or completion), and 3) skilled (beyond high school through completion of an advanced degree). Most job referrals (80 percent) went to semiskilled workers, while only 10 percent were in the skilled group. The magnitude of the effect of job referrals on the probability of finding a job within three months decreases signficantly as educational attainment increases. This means that, relatively, SINE job referrals benefit less-skilled job seekers the most. While their effects were not significantly different from those of semiskilled and skilled job seekers, the unskilled did see bigger reductions in the time until reemployment. The semiskilled had the smallest reductions in reemployment job tenure, significantly smaller than for skilled job seekers, but not very different from the unskilled. The impact on reemployment wages of a SINE job referral was significantly smaller for the unskilled (−1.9 percent) than for the semiskilled (−6.1

[41] Paixão et al. (2012) show that RAIS, in 2009, identifies 61.2 percent of individuals as white, while PNAD identifies 54.7 percent of workers as white. Câmara (2015) shows that 2010 RAIS data identifies 60 percent of workers as white, and the 2010 census only identifies 53 percent of workers as white. Race in the RAIS data presents five categories (indigenous, white, dark, yellow, brown). For Table 9, we divide the data into white and nonwhite.

percent) and the skilled (−23.5 percent). The negative effect on the wages of the highly skilled might signal incapacity on the part of SINE to attract high-quality vacancies. As other researchers have found for other countries, our evidence suggests SINE job referrals are particularly valuable for the unskilled.

Table 6 Estimates of SINE Job Interview Referral Impacts on Four Outcomes by Subgroup for Samples Partitioned by Age, Sex, Race, and Skill Level, Based on Educational Attainment

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment wage (log)
AGE 18–24	0.226***	−2.330***	−2.096***	−0.0414***
	(0.012)	(0.103)	(0.116)	(0.003)
Observations	3,928,116	1,761,790	2,657,300	2,649,949
AGE 25–34	0.267***	−3.107***	−2.762***	−0.0592***
	(0.008)	(0.108)	(0.240)	(0.006)
Observations	8,366,676	4,570,504	5,728,910	5,713,302
AGE 35–44	0.265***	−3.185***	−3.398***	−0.0556***
	(0.009)	(0.127)	(0.449)	(0.008)
Observations	4,808,100	2,431,800	3,041,026	3,032,629
AGE 45–54	0.254***	−3.105***	−4.919***	−0.0523***
	(0.009)	(0.152)	(0.584)	(0.009)
Observations	2,416,680	1,130,826	1,401,982	1,398,012
AGE 55–64	0.242***	−3.884***	−6.950***	−0.0502***
	(0.010)	(0.185)	(0.488)	(0.010)
Observations	779,760	337,192	391,184	390,046
MALE	0.275***	−3.180***	−4.028***	−0.0639***
	(0.009)	(0.094)	(0.365)	(0.009)
Observations	11,707,680	6,339,806	7,858,306	7,837,233
FEMALE	0.238***	−3.836***	−4.213***	−0.0654***
	(0.009)	(0.124)	(0.303)	(0.005)
Observations	8,678,488	3,684,396	5,363,858	5,348,523
WHITE	0.260***	−3.750***	−4.503***	−0.0778***
	(0.011)	(0.138)	(0.366)	(0.008)
Observations	9,585,256	4,642,246	6,250,658	6,232,846
NONWHITE	0.259***	−3.207***	−3.696***	−0.0516***
	(0.007)	(0.099)	(0.287)	(0.006)

Observations	10,800,780	5,392,306	6,968,744	6,950,172
UNSKILLED	0.287***	−3.686***	−4.237***	−0.0191**
	(0.010)	(0.184)	(0.485)	(0.008)
Observations	3,368,556	1,679,206	2,144,906	3,368,556
SEMI-SKILLED	0.254***	−3.400***	−3.952***	−0.0614***
	(0.009)	(0.100)	(0.318)	(0.006)
Observations	16,202,160	7,965,430	10,577,488	10,549,066
SKILLED	0.240***	−3.304***	−5.765***	−0.235***
	(0.011)	(0.162)	(0.399)	(0.014)
Observations	815,440	398,982	503,476	502,265

NOTE: Standard errors in parentheses. * = $p < 0.10$; ** = $p < 0.05$; *** = $p < 0.01$.
SOURCE: Authors' calculations.

5.3 Effects by Unemployment Insurance Recipiency and Unemployment Duration

The analysis based on unemployment insurance (UI) status is relevant because the effectiveness of the service for UI beneficiaries might be different, and there is evidence that access to UI affects incentives for formal employment. Tatsiramos (2014) points out that UI systems can increase reservation wage and lead to longer unemployment spells. However, UI benefits can provide the conditions for UI beneficiaries to increase the quality of the job found. Furthermore, Carvalho et al. (2018), Van Doornik et al. (2018), and Cravo et al. (2020) find that Brazil's formal-sector workers who have access to UI have the ability and incentives to induce their own dismissal to some extent.

Table 7 shows the results of the analysis of the effect of SINE referrals on UI beneficiaries versus nonbeneficiaries. A SINE job referral has larger impacts on non-UI beneficiaries than it does on UI beneficiaries. Non-UI beneficiaries have a significantly higher increase in the probability of getting a job within three months of a job referral, and their reduction in time until reemployment is larger by a half month; however, the reduction in reemployment job tenure is similar for UI and non-UI beneficiaries. Furthermore, the reduction in the reemployment wage is larger for non-UI beneficiaries. The effectiveness of SINE job referrals for UI beneficiaries might be affected by higher reservation wages, allowing workers to look for jobs for longer periods and find a better job match that preserves previous wage levels.[42]

The long-term unemployed form an especially vulnerable group of applicants, defined as people who have been unemployed for more than 12 months. Results for this group go in the same direction of general regressions but show differences in the magnitude of the effects. The effect of SINE job referrals is stronger for this group in terms of the likelihood of finding a job within three months and the time it takes to get a job, which is 1.6 months shorter than for long-term unemployed who did not get a SINE job referral. Nevertheless, the negative impact on wages is more pronounced for long-term unemployment, as finding a job through a SINE job referral reduces wages by about 10 percent. While deeper investigation is warranted, SINE job referrals appear to be an effective means of reducing long-term unemployment.

Thus, the results for the analysis based on unemployment status show heterogeneity in the impact of the labor intermediation process. In particular, UI benefits may affect the results of the labor intermediation process, which has implications for unemployment spells and the quality of the job matching. While deeper investigation is warranted, SINE job referrals appear to be an effective means of reducing long-term unemployment.

[42] Despite efforts of the government to further integrate the labor intermediation and unemployment insurance policies, legislation is not effective to induce UI beneficiaries to quickly accept job offers obtained through the labor intermediation process. Federal Law No. 12.513, from 2011, states that labor intermediation services and unemployment insurance should work in an integrated manner. It indicates that the UI benefit can be canceled in the case of a worker not accepting a job that is "suitable" according to the worker's qualifications and past experiences. In practice, UI benefits are *not* canceled, as "suitable" is not clearly defined in regulations and the law is weakly enforced.

Table 7 Effects of SINE Referrals by UI Receipt and Unemployment Duration

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment wage (log)
UI beneficiaries	0.207***	−2.533***	−2.795***	−0.0288***
	(0.00781)	(0.103)	(0.486)	(0.00509)
Observations	2,157,364	1,123,086	1,666,510	1,663,046
Non-UI beneficiaries	0.227***	−3.131***	−2.754***	−0.0545***
	(0.0108)	(0.0869)	(0.144)	(0.00523)
Observations	11,483,120	5,808,344	7,532,858	7,510,053
Long-term unemployed	0.298***	−2.122***	−4.974***	−0.0995***
	(0.00901)	(0.0938)	(0.503)	(0.0111)
Observations	7,125,368	2,329,738	4,555,288	4,544,947

NOTE: Standard errors in parentheses. * = $p < 0.10$; ** = $p < 0.05$; *** = $p < 0.01$.
SOURCE: Authors' calculations.

5.4 Staff-Assisted versus Self-Service Job Referrals

Technology is changing the manner in which public services are provided. Digital channels for labor intermediation have been adopeted in many countries; these contribute to the effectiveness and efficiency of the public employment service. Nevertheless, to our knowledge, little empirical evidence is available on how mobile technologies impact labor intermediation services and employment outcomes. Dammert et al. (2015) provide one exception and designed an experiment to assess the causal impacts of digital public labor-market intermediation in Peru. The authors suggest that the use of digital technologies in the public labor intermediation system increases the probability of finding employment in the short term.

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 also with respect to the quality of such placements. This is an important aspect of 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 8 shows the effect of having SINE online referrals for one group versus the effect of using face-to-face referrals for a control group.

The results from Table 8 show that the probability of getting a job within three months is not statistically different if the referral is online. However, the time until employment after the referral is 0.6 months longer, suggesting that the face-to-face service is more effective. On the other hand, for those who obtain a job, the mean tenure is 0.5 months longer, and the reemployment wage is 1 percent higher. Thus, our results suggest that face-to-face referrals are more effective than online service to obtain employment faster, but that job matching seems to be more efficient through online services, as reemployment wages are higher and job tenure is longer.

Table 8 — Effects of SINE Internet Referrals

	Employment within 3 months	Time until employment (months)	Mean tenure (months)	Reemployment wage (log)
Effect from SINE (control group from face-to-face job interview referrals)	0.00435 (0.0103)	0.569*** (0.135)	0.540** (0.248)	0.0124** (0.00513)
Observations	283,872	185,924	198,560	198,079

NOTE: Standard errors in parentheses. * = p < 0.10; ** = p < 0.05; *** = p < 0.01. Results presented in this table should be interpreted with caution because of a shorter time span, as Internet-based referrals only started in 2014.
SOURCE: Authors' calculations.

6 Conclusion

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

Using data from January 2012 to December 2016, we construct matched pairs comparison groups and compute difference-in-difference regressions to measure SINE's impact on the four labor market outcomes. Overall, SINE job interview referrals increase the likelihood of reemployment in the first three months following referral and decrease the time to reemployment. Being referred by SINE has bigger effects for less-skilled workers than it does for more highly skilled workers.

However, a job interview referral by SINE appears to reduce the job tenure in the new job and the monthly salary on that job. 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 of our study provide a clearer explanation of how SINE functions, and thus can contribute to the design of better labor market policy. The heterogeneity of SINE's impact on different subgroups suggests that providing specific support to each group of customers might improve the effectiveness of labor intermediation services. The use of technology in doing job interview referrals through the web contributes to the placement of workers, but face-to-face services have a greater impact on shortening the time until employment. Thus, there appears to be room for technological improvement in the matching algorithm used for online services; such improvement could reduce the gap between face-to-face and remote services. A combination of services, provided at a SINE office as well as remotely, should be considered to increase the cost-effectiveness of the SINE network while maintaining its impact.

The heterogeneous effects of SINE on different groups of customers call for a more tailored approach to increase both the effectiveness and the efficiency of the intermediation services. Additional research is needed to understand the most cost-efficient combination of online and face-to-face services.

APPENDIX

Appendix A: Descriptive Statistics

Table A1
Effectiveness — 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

SOURCE: Authors' calculations.

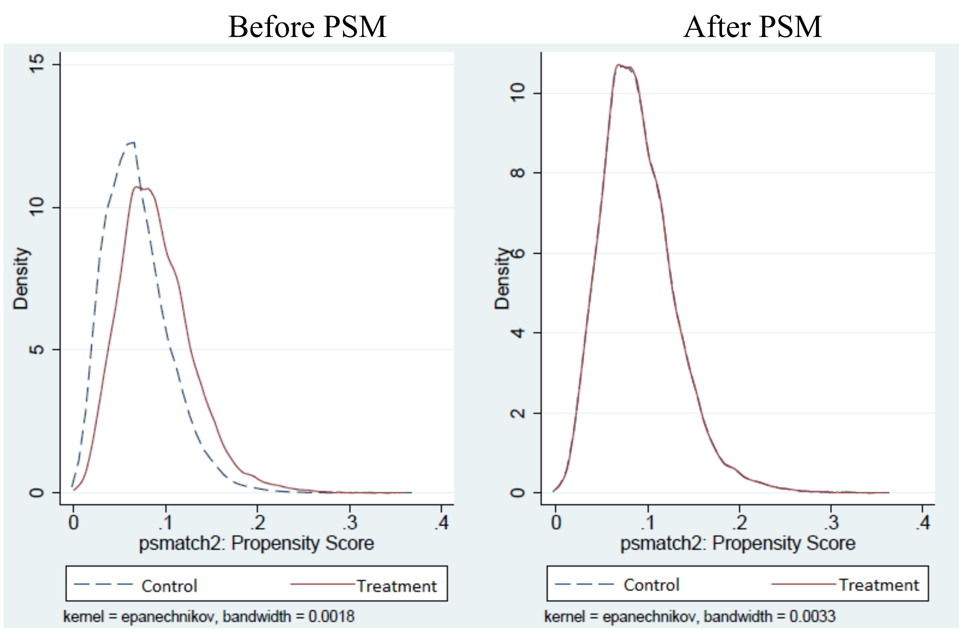
Table A2
Placed Referrals by Worker Status

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

SOURCE: Authors' calculations.

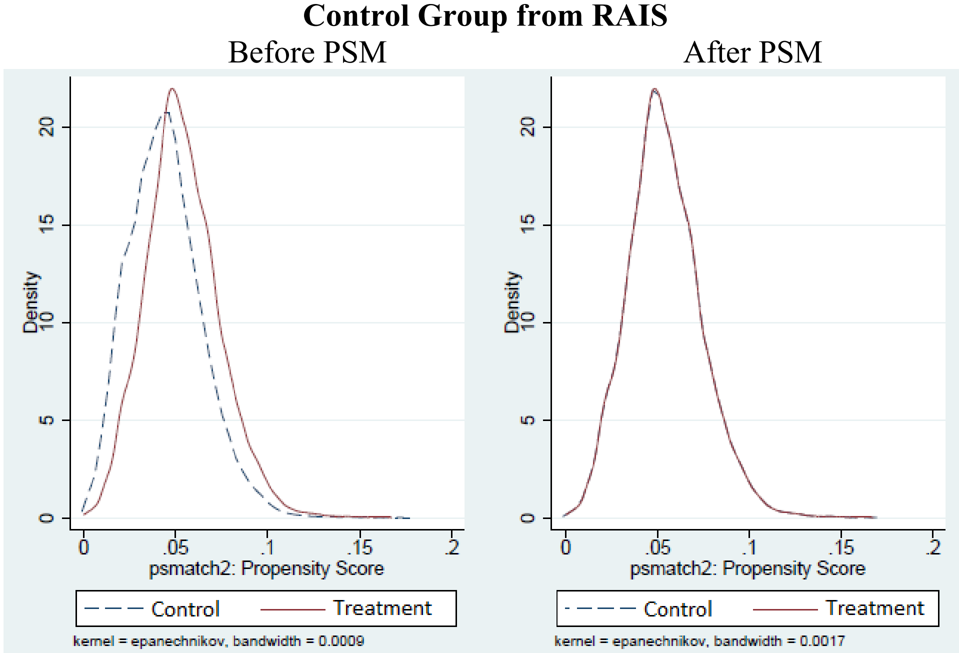
Appendix B: Matching Quality

Figure B1 — Kernel Density, January 2012, Control Group from SINE



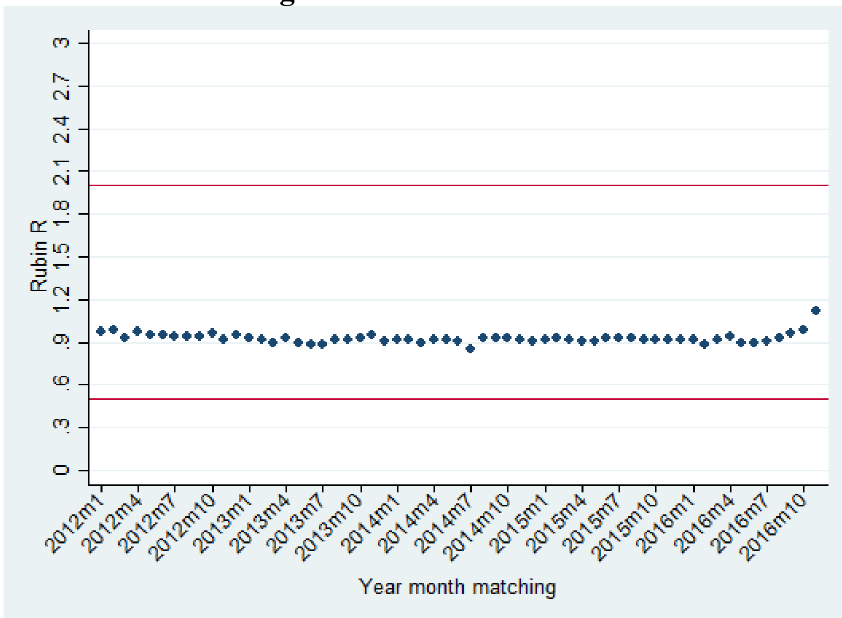
SOURCE: Authors' calculations.

Figure B2 — Kernel Density, January 2012, Control Group from RAIS



SOURCE: Authors' calculations.

Figure B3 — Rubin *R* test



SOURCE: Authors' calculations.

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)
Effect from SINE (relative to control)	0.227***	−2.577***	−2.913***	−0.0543***
	(0.0109)	(0.164)	(0.231)	(0.00535)
Observations	20,386,188	10,688,984	14,010,724	13,975,252

NOTE: Standard errors in parentheses. * = p < 0.10; ** = p < 0.05; *** = p < 0.01. The alternative subgroup regressions using the RAIS control group are available upon request. Control group constructed based on RAIS data alone.
SOURCE: Authors' calculations.

Appendix D: Mean Outcomes Post-Matching

Table D1 — Mean Outcomes Post-Matching

Control Group from SINE	Control	Treatment
Employment within 3 months	0.24	0.44
Time until employment (months)	8.00	5.19
Mean tenure (months)	10.48	6.88
Reemployment wage (R$)	1,453.18	1,344.66

NOTE: Means are computed over the whole sample combined over all 60 months for the control and treatment groups after propensity score matching in each month.
SOURCE: Authors' calculations.

Appendix E: Effect of SINE for Referrals by Year

Table E1 — Effect of SINE for Referrals by Year, 2012 to 2016

	2012	2013	2014	2015	2016
Employment (within 3 months)	0.202***	0.207***	0.199***	0.178***	0.223***
	(0.0132)	(0.00845)	(0.00914)	(0.0104)	(0.00939)
Observations	3,996,852	4,677,940	4,505,288	4,412,672	2,766,484
Time until Employment (months)	−1.298***	−1.116***	−0.929***	−0.322	1.265***
	(0.208)	(0.180)	(0.231)	(0.197)	(0.294)
Observations	1,107,418	1,833,532	2,111,832	2,302,360	1,878,042
Mean tenure (months)	−2.584***	−2.640***	−2.599***	−2.463***	−4.899***
	(0.107)	(0.157)	(0.204)	(0.408)	(0.470)
Observations	3,632,718	4,022,058	3,417,662	2,563,564	1,102,522
Reemployment Wage (log)	−0.0673***	−0.0577***	−0.0454***	−0.0400***	−0.0440***
	(0.00544)	(0.00607)	(0.00640)	(0.00607)	(0.00853)
Observations	3,623,904	4,012,322	3,407,757	2,555,778	1,099,766

NOTE: Standard errors in parentheses. * = p < 0.10; ** = p < 0.05; *** = p < 0.01.
SOURCE: Authors' calculations.

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