CHRISTOPHER O'LEARY
W. E. Upjohn Institute for Employment Research, United States

TÚLIO CRAVO
African Development Bank, Ivory Coast

ANA CRISTINA SIERRA
World Bank, United States

LEANDRO JUSTINO
World Bank, United States

Effects of Job Referrals on Labor Market Outcomes in Brazil

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 (2012–16) 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 is less effective than the in-person job interview referrals provided at SINE offices.

JEL Codes: J18, J23, J68

Keywords: Labor market policy, employment services, job interview referrals, difference-in-differences

Countries in Latin America and the Caribbean 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 region, labor market programs have garnered a bigger share of public resources and have served more job seekers and employers (Ramos, 2002).

In Brazil, labor markets have performed reasonably well over the past fifteen years in terms of labor market participation and labor earnings growth.

ACKNOWLEDGMENTS We are grateful to the reviewers and the editor for helpful comments. Financial support from the Inter-American Development Bank for an earlier version of the paper and from the W. E. Upjohn Institute for Employment Research is acknowledged. We thank the Ministry of Labor, Brazil, for providing access to the data.

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 12.0 percent in the subsequent four years.[1]

The country's National Employment System (SINE) is a key institution for public employment policies. Created in 1975, this network of local employment offices serves as a go-between, helping workers line up jobs 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, covering all twenty-six states and the Federal District. The Ministry of Labor coordinates this large network, monitoring the decentralized delivery of services by states and municipalities.[3]

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, using propensity score matching (PSM) to create comparison groups and difference-in-differences estimators to compute impacts, 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 educated 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 Latin American and Caribbean countries (Aedo and Walker, 2012).

Improving the effectiveness of the public employment service (PES) is essential to supporting quick, successful, and durable job matches (Betcherman, Olivas, and Dar, 2004). An effective PES contributes to labor market efficiency, reducing informational breakdowns that slow or prevent the proper matching of job seekers' skills to employers' job vacancies. Borges, Lobo, and Foguel

1. According to the Brazilian Business Cycle Dating Committee (CODACE) of the Brazilian Institute of Economics (IBRE), the recession lasted eleven quarters, from the second quarter of 2014 to the last quarter of 2016.

2. SINE was created after the Brazilian government ratified Convention No. 88 of the International Labour 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 on SINE, see IPEA (2020) and Lobo and Anze (2016).

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.

(2017) estimate that PES labor intermediation in Brazil saved the Worker Protection Fund about R$43 million in 2016 through reduced unemployment insurance payments. Since labor intermediation programs typically benefit low-skilled workers, countries with a large proportion of such job seekers could benefit from increased investment in labor exchange services.

As a percentage of the total budget for all active labor market programs, spending on labor intermediation services in Brazil is low compared to members of the Organization for Economic Cooperation and Development (OECD): Brazil spends less than 2 percent on labor intermediation services, while OECD countries spend an average of 10 percent (Silva, Almeida, and Strokova, 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 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.

When one considers 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 positive evidence of effectiveness for public labor exchange services in those developed countries (Blundell and others, 2004; Johnson, Dickinson, and West, 1985; 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 America showing causal evidence from survey data provide mixed results. Vera (2013), based on a small survey of 150 job applicants, finds that PES participation in Peru lengthens unemployment spells by thirty-three days. Pignatti (2016), using a nationwide survey for Colombia, finds that the Colombian PES increased participants' likelihood of having a formal job by between five and thirty-one 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 for 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 observational data to produce a more robust evaluation of a labor intermediation service. Using administrative microdata from 2012 to 2016, our study uses PSM to create comparison groups and difference-in-differences estimators to compute impacts of SINE job referrals on labor market outcomes. Our difference-in-differences estimates suggest 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 wage of the next job. Our paper shows two other things: SINE job referral impacts differ across subgroups, and web-based job interview referrals contribute to the placement of workers but are less effective than face-to-face services in shortening nonemployment spells. Knowledge of these results can help program administrators design strategies to improve labor intermediation services.

The remainder of this paper is structured as follows. After summarizing the related literature, we describe the data used in the analysis and present summary statistics. Subsequent sections detail our methodology and present our results. The final section offers concluding remarks.

Background

Previous researchers provide 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. Attempts to assess the impact of job interview referrals in the United States and Europe date back to the 1980s (for example, Johnson, Dickinson, and West, 1985; Jacobson and Petta, 2000), but the early U.S. studies did not provide convincing causal evidence of effectiveness.

More recently, Blundell and others (2004) used differences in the geographic location and demographic targeting of services to convincingly identify the effect of the New Deal for Young People program in the United Kingdom, which provided compulsory job search assistance to unemployment compensation applicants and wage subsidies to employers. The authors provide causal evidence that job search assistance increased the probability of young men finding a job in the next four months by five percentage points. This impact diminished over time, perhaps because of displacement effects.

Crépon and others (2013) used 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 that even though the program increased the likelihood of finding a stable job, the positive effect diminished over time and often came at the expense of other eligible workers. However, the SINE facilitates only about 3 percent of job placements, suggesting that displacement effects are a smaller concern in Brazil.

A more recent randomized controlled trial in the United States during the Great Recession identified unemployment insurance applicants who were likely to exhaust benefits and randomly assigned them to eligibility assessment, job search assistance, or nothing (Michaelides and Mueser, 2018). Strong causal evidence suggests that 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 results suggest that actions targeting unemployment insurance recipients can enhance labor intermediation services.

Few studies explore the effectiveness of PES agencies in South America. Vera (2013) conducted one study in Peru using a quasi-experimental design and finds that job search assistance provided by the Peruvian PES had only small impacts on unemployment spells compared with job search assistance from private agencies. However, her research design has important limitations for generating convincing causal evidence: the treated sample was based on information on program beneficiaries collected from a survey distributed to only 150 job applicants whom the PES had placed in a job in September 2004.

Pignatti (2016) used PSM to identify causal effects of job placements by the Colombian PES relative to job placements by other means such as private agencies, public posting of job openings, newspaper or website advertisements, or family and friends. Based on data from the annual household survey (*Gran Encuesta Integrada de Hogares*) conducted by the National Administrative Department for Statistics, the study finds evidence suggesting that using the Colombian PES positively affects the probability of having a formal sector job. However, it also finds that PES job placements reduce earnings in Colombia. A limitation to the identification strategy is that Pignatti's (2016) data were based on a sample of PES users from a general household survey, meaning the data do not have a panel structure and do not provide detailed information on previous job search history.

Our paper relies on the full population of all PES users in Brazil, merged with longitudinal data on employment and earnings from the Annual Social Information Report (*Relação Anual de Informações Sociais*, RAIS). It is, to our knowledge, the most complete evaluation of labor intermediation conducted in Latin America. Therefore, unlike previous analyses for Latin America, we are able to directly investigate the effects of program participation on the probability of finding a job, since our unique data set allowed us to follow job seekers' labor history both before and after the SINE job interview referral.

Only the prior study by Woltermann (2002) attempts to assess the effectiveness of job interview referrals on different groups of participants in Brazil. The study finds that the only significant channels for transition into formal sector jobs are directly contacting the employer, using connections through family and friends, and responding to advertisements. 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, although the literature from Europe and the United States provides more credible results about labor intermediation programs, the existing literature in Latin America does not provide convincing impact evaluations of the effectiveness of such programs on employment probability, earnings, time until reemployment, and job tenure. This paper constitutes the most comprehensive attempt to date to understand the effectiveness of these nationwide labor market programs in the Latin American context, using administrative data from Brazil for the first time.

Data and Descriptive Statistics

We constructed a unique data set, merging administrative data from SINE with data from the RAIS to analyze the effectiveness of labor intermediation in Brazil. 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 interview referrals, job placement, labor market information, issuance of formal worker-identification credentials, and some components of the unemployment insurance program, including benefit payments.[4]

The intermediation process involves the registration of workers and employers, recording of the employment histories of job seekers, and listing of job vacancies. The process of SINE labor intermediation begins with job search registration at a SINE office or through the SINE website. Based on information in the SINE database, the labor exchange officer explores possible job matches between the profiles of registered job seekers and listings

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

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 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.

The SINE 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 research purposes here for the first time, contains socioeconomic information on workers 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), which 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 data include employment and earnings information on all formal sector 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 (including wage, tenure, type of employment, hiring and separation dates, and reason for separation). Importantly, RAIS is an employer-employee matched data set that can be linked to the SINE data set using the 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

5. A worker who is a beneficiary of the unemployment insurance benefit cannot refuse an interview referral without having an acceptable excuse (Federal Law No. 7,998 of 1990).

6. In 2016, online self-referrals accounted for 16 percent of the total number of referrals (see table 1). IPEA (2014) shows details of the flow chart of the SINE labor intermediation process.

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.

data to construct a monthly panel with information on 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—that is, multiple jobholders. Since job loss for a multiple jobholder does not result in full unemployment, our sample excludes workers who at some point in our data period had multiple simultaneous formal sector jobs.[9]

Since most workers who seek assistance from SINE 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 sector employment histories and at least one month of nonemployment 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. Naturally, sequential job holding is permitted in our sample, because a new job *after* the job interview referral is a positive outcome (for example, 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.[12] In these data, we observe about 95,000 job interview referrals each month. The average reemployment job tenure is less

8. Outcomes are measured using RAIS records that encompass only 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 period with no 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 sector 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 for 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.

12. The resulting panel includes 29 million workers with at least one unemployment spell and a total of 41 million unemployment spells, as some workers have more than one unemployment spell.

TABLE 1. Descriptive Statistics of SINE Labor Intermediation, 2012–16

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

Source: Authors' calculations, based on data from the Brazilian Ministry of Labor.
Note: The placement rate is equal to the ratio of workers placed to referrals.

than two years, suggesting that the available five-year time span for the data is sufficient to measure reemployment job tenure.[13]

Combining the SINE and RAIS data sets allows us to trace the duration of formal sector employment, time until reemployment, and earnings on the new job for individuals who look for employment through SINE agencies compared with 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 that improved data quality and reliability significantly, according to the Ministry of Labor. Table 1 shows that the total number of unique workers registered in the SINE system reached 31.4 million for the 2012–16 period.[14] While 70 percent of the vacancies available at SINE have at least one job interview referral, only 28 percent of the vacancies were filled through a SINE job referral.[15] The overall placement rate (workers placed by referral) of SINE is about 12 percent throughout the period of analysis. Online self-service referrals were permitted starting in 2014.

13. The average job tenure in these data is exactly 19.6 months. The average job tenure for the formal private sector in Brazil is about 3.5 years, according to DIEESE (2016).

14. Table 1 shows the number of new SINE registrants per year. For instance, in 2016, 4,587,164 workers who had never registered with SINE did so. Thus, 31.7 million is the number of unique workers registered.

15. 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 ten employees. On average, 3.8 positions are offered for 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 2. Descriptive Statistics for Job Seekers Referred by SINE, 2015

	Observations	
Statistic	*Employed*	*Unemployed*
Percent of total observations	6	94
Age, sample mean	24.1	31.7
Race (%)		
Indigenous	0	0
White	38	42
Dark	11	12
Yellow	1	1
Brown	49	45
Education (%)		
Illiterate	0	0
Incomplete middle school	9	15
Middle school graduate	6	11
Incomplete high school	29	14
High school graduate	46	49
Incomplete college	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.

To evaluate the impact of labor intermediation, we construct a monthly database with PSMs of job seekers getting referrals to other unemployed workers not getting referrals. We used data on only the first referral each month per unemployed job seeker, even if that individual was referred more than once in a month.[16]

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. 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 referrals is about thirty years old. While

16. 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 online appendix A, table A1). (Supplementary material for this paper is available online at http://economia.lacea.org/contents.htm.)

TABLE 3. Descriptive Statistics of SINE Labor Intermediation by State, 2012–16

State	*Workers registered*	*Offices per state*	*Vacancies*	*Referrals per office*	*Placements per office*	*Placement rate (%)*
Acre	80,247	11	8,832	2,008	395	19.7
Alagoas	393,550	43	137,497	4,316	1,984	46.0
Amapá	83,460	12	12,673	1,461	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
Distrito Federal	501,929	26	233,878	41,793	2,492	6.0
Espírito Santo	642,186	34	185,039	11,152	792	7.1
Goiás	1,150,209	90	419,242	11,468	1,005	8.8
Maranhão	552,293	47	49,209	1,990	674	33.8
Mato Grosso	569,393	45	250,436	10,416	2,067	19.8
Mato Grosso do Sul	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	488	23.0
Paraíba	430,538	40	99,891	5,207	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	254	13.8
Rio de Janeiro	2,362,499	127	1,013,274	8,708	922	10.6
Rio Grande do Norte	379,473	38	36,130	2,307	195	8.5
Rio Grande do Sul	1,791,515	128	662,611	14,273	1,519	10.6
Rondônia	234,515	20	52050	6,221	921	14.8
Roraima	61,362	7	9,081	5,880	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	245	7.9
Tocantins	212,324	16	139,568	22,394	4,002	17.9
Total	31,424,197	1,930	12,295,072	14,098	1,697	12.0

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

almost 50 percent of the unemployed job seekers are high school graduates, fewer than 11 percent have any college education. Fifty-eight percent of the unemployed job seekers getting referrals are male, and 61 percent are considered nonwhite.

Brazil is well known for having wide regional cultural and economic variation, and this variation extends to the SINE system. Table 3 summarizes regional differences across Brazilian states when it comes to the provision of services in SINE offices. These heterogeneities suggest that differences across states should be considered in the process of estimating the impacts of SINE services.

Methodology

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 job interview referrals by SINE offices on the labor market outcomes of recipients relative to nonrecipients. However, simple differences of means between recipients and nonrecipients will not yield causal estimates of program effects because the characteristics of the two groups are likely to differ, owing to self-selection into SINE registration and services.

The evaluation problem is to compare workers who received a SINE job referral to their counterfactuals without a job referral. The challenge is to make sure the counterfactual is properly selected. SINE services match workers to vacancies based on a list of criteria, and this automated process with mediation by SINE staff 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—the ideal counterfactual. In this study, we use PSM to construct a counterfactual for the group getting referrals—the participant group—by selecting a group of registered workers who are not getting referrals but who have a similar pretreatment conditional probability of receiving a referral—the comparison group. We then estimate group mean effects, or the average treatment effect on the treated, as a difference in mean outcomes between these two groups. The individuals in the matched comparison group will be similar to the participants in terms of observed characteristics, except for the referral. The application of PSM requires satisfying 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, conditional on a set of observed attributes, the distribution of the (counterfactual) nontreatment outcome in the treated group is the same as 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 and others (2004) and Heinrich, Maffioli, and Vázquez (2010).

The propensity scores used to balance characteristics between participant (referrals) and comparison (not referred) groups are estimated using the following probit model for each subgroup evaluated:

$$(1) \qquad P\left(D = 1 \middle| \mathbf{X}\right) = \phi\Big[\beta\mathbf{X} + \gamma\Big(Age + Job_{tenure} + \log Wage + Gender + Unemployment\_spell\Big)D_{region}\Big].$$

In this specification, we calculate the probability of being referred for a job interview, $P(D = 1|\mathbf{X})$, as a function of observable individual characteristics. Importantly, our data include 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 sixty 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]

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 the Results section, sixty PSM models were estimated, thus creating different common supports with a different number of observations.

21. Sianesi (2004) evaluates employment services in Sweden and develops 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 those 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, Maffioli, and Vázquez, 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 months), the logarithm of the average monthly wage 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 eleven categories), industrial sector (eighty-six CNAE categories at the two-digit level) and occupational group (forty-eight CBO categories at the two-digit-level) of the person's last job, and number of months unemployed.[23] In addition, as shown in equation 1, age, job tenure, wage, gender, and unemployment duration are interacted with region dummy variables.[24] Tenure in the last job before referral (months) and the logarithm of the average monthly wage at the last job were included in the PSM to reduce selection on unobservables, as these variables encompass information on unobservables (Heinrich, Maffioli, and Vázquez, 2010).

We construct control groups using the pool of workers who 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 because of unobservable characteristics, such as their level of self-motivation and general proactiveness.[25] Additionally, we require the common support condition to be met exactly.

After estimating propensity score models, the next step is to perform the matching and assess its quality. The literature suggests that observable

23. CNAE is the national classification of economic activities; CBO, the national classification of professions. Since the large number of observations allows, we also estimated an alternative PSM whereby individuals are matched with certainty on two characteristics: the number of months unemployed until matching and 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 on 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.

24. Heinrich, Maffioli, and Vázquez (2010) suggest that in a scenario with a limited number of variables, to obtain a balance between treatment and control groups, interactions with an available variable can improve the matching. We interact the vector **X** with regions to achieve an improved matching model.

25. The information used in the PSM to construct control groups always comes from RAIS. While the main database used to compare the referred versus 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

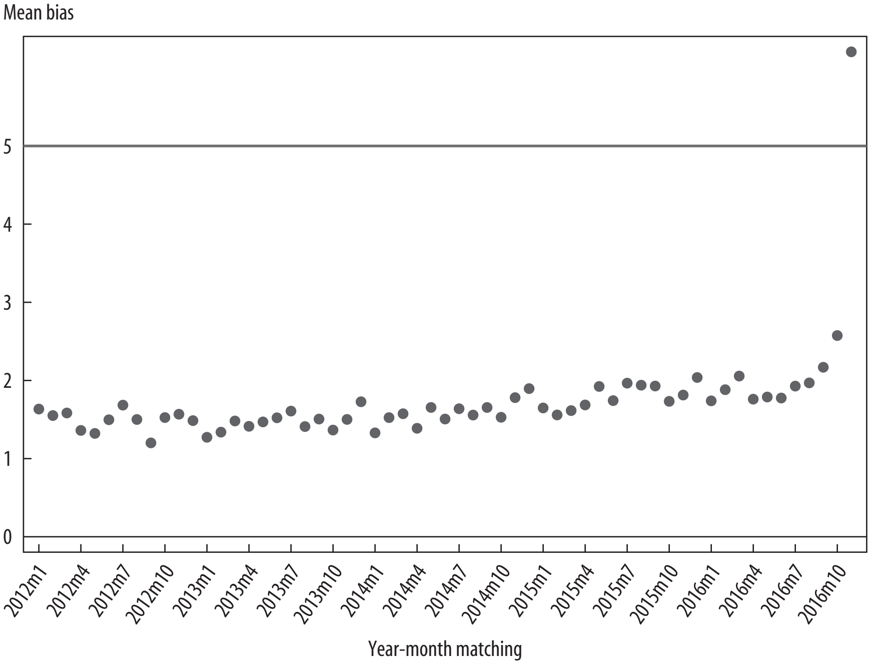
		Mean		Bias reduction			
Variable	*Sample*	*Treated*	*Control*	*Bias (%)*	*(%)*	*t test*	$P > \|t\|$
Male	Unmatched	0.549	0.583	7.050		20.064	0.00
	Matched	0.584	0.580	0.640	90.89	1.461	0.14
Age	Unmatched	31.474	32.831	12.580		36.922	0.00
	Matched	32.864	32.862	−0.270	97.78	−0.635	0.53
Tenure last job	Unmatched	24.073	15.594	−28.230		−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 completed	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 completed	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 completed	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 completed	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.

Note: The treatment or participant group is made up of workers registered with SINE who received a referral for a job interview; the control or comparison group is made up of workers registered with SINE who did not receive a referral for a job interview in January 2016. The bias for a given variable is defined as the difference between the means of the treatment and control groups, scaled by the average variance.

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 indicate that before matching, the participant and comparison groups are sigificantly different on most observable characteristics, but after matching

FIGURE 1. Mean Standardized Bias between Participant and Comparison Groups Post-Matching



Source: Authors' calculations.
Notes: Each dot in the figure represents the mean standardized bias between control and treatment groups for each month of the data. The solid line marks the threshold of 5 percent final bias.

there are few significant differences. This suggests that the participant and nonparticipant matched samples are well balanced.

The matching does not necessarily need to yield complete balance on all exogenous variables to be satisfactory. We use the mean standardized bias to formally assess the quality of the PSM. If the matching process improves balance on observable characteristics between the participant and comparison groups, it is expected that the mean standardized bias between the two groups will be significantly reduced. According to empirical studies, a final bias below 5 percent after matching should be sufficient (Caliendo and Kopeinig, 2008). Figure 1 plots the value of the mean standardized bias calculated separately for each month. In this case, the bias maintains an average value of 1.7 after the matching, an indication of the good quality of the PSM.[26] 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 online appendix B).[27] 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]

We use the participant and comparison groups constructed by PSM to measure impacts on the following labor market outcomes: probability of employment within three months, time from registration until employment, job tenure in the new job, and reemployment monthly earnings. As described earlier, 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.

Measuring SINE Impact on Labor Market Outcomes

Having used propensity score matching to construct counterfactual groups for workers who had a SINE job interview referral, which were validated by three tests, we use the participant and constructed comparison groups in the following difference-in-differences specification to estimate the impact of a job interview referral on labor market outcomes for worker *i*:

$$(2) \qquad Y_{it} = \phi + \alpha Treated_i + \gamma Post_{it} + \theta SINE_{it} + \beta \mathbf{X}_{it} + \mu_t + \varepsilon_{it},$$

where Y_{it} stands for one of the four outcome measures for individual i and time t. *Employment within three 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 zero for the pre-matching

26. 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 sixty months (see figure B3 in the online appendix).

27. Supplementary material for this paper is available online at http://economia.lacea.org/contents.htm.

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 on request.

period.[29] *Time until employment* is period of unemployment 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 number of months in the reemployment job, and *reemployment wage* is the natural logarithm of the real wage on the reemployment job.[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 one 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 workers who are not included in the PSM.[32] We also include information on whether the worker is a beneficiary of unemployment insurance, dummy variables for the *n*th unemployment insurance payment, and the total number of referrals.[33] Standard errors for statistical inference are computed with clustering at the state level.[34]

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 require the observation of one job before and after matching to measure the outcomes; no further restrictions are imposed. In contrast to the method used to calculate the time until employment, the information on job tenure is observed in the record of employment prior to job search and does not need to be constructed from observing two jobs prior to the matching. Tenure of the reemployment job is computed as the difference between the job start and end dates.

32. Education is disaggregated into three categories: unskilled (from illiterate to completed primary school), semiskilled (partial or completed high school), and skilled (any tertiary education). 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-differences estimations, as they were not available when the main bulk of the PSM was calculated. Alternative estimations including these variables in the PSM or difference-in-differences estimations, without the variables included in vector **X**, provide similar results.

34. We assume that the observations are independent across states as labor market institutions differ. For instance, even though the minimum wage is defined nationally, each state in Brazil can set its own minimum wage above the national minimum wage, which can influence labor market dynamics. Regarding the SINE service, even though SINE is coordinated at the central level, each state manages its own SINE network and might apply different resources and managerial procedures.

TABLE 5. Effect of SINE Job Interview Referrals on Labor Market Outcomes

Description	*Employment within three months*	*Time until employment (months)*	*Mean tenure (months)*	*Reemployment wage (log)*
Effect of SINE Standard error	0.200***	−0.452**	−3.533***	−0.058***
	(0.010)	(0.173)	(0.233)	(0.006)
No. observations	20,359,236	9,233,184	14,738,524	14,699,527

Source: Authors' calculations.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.
Note: The table shows the difference-in-differences estimates of the effect of SINE job referral on labor market outcomes. Standard errors clustered at the state level are in parentheses.

Results

The analysis seeks to measure the effect of job interview referrals on the probability of workers finding a job within three months of the referral, the time until employment, the mean tenure in the next job, and the reemployment wage. Impacts are computed by comparing outcomes of workers who received SINE job referrals to those of a matched comparison group of workers who were registered with SINE but did not get a job referral.[35]

The results show that the treatment increases the likelihood of finding a job within three months of the referral by 20.0 percentage points (see table 5). 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.[36] 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 eight months, on average. However, SINE job referrals have a negative impact on the mean tenure in the next job found. On average, job tenure is reduced by 3.5 months, which equates to an 18 percent reduction in the average job tenure of 19.6 months found in the data.[37] Finally, being treated by SINE reduces wages by about 5.8 percent.

The result that a SINE job referral is associated with a wage reduction is consistent with Pignatti (2016) and Vera (2013) and may be due to stigmatization

35. Results using RAIS for control groups are very similar and are provided in online appendix C.

36. Online appendix C provides an indication of the size of the employment's system'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.

37. See footnote 12.

effects on SINE participants or a lack of capacity by the program to attract high-paying enterprises to the system.[38] Also, SINE job referrals promote faster reemployment, since SINE mainly lists low-wage jobs that have short tenure. This result is consistent with suggestions from job search and matching models that heterogeneous preferences for job amenities will be reflected in the distribution of reemployment wages and other attributes such as job durability (for example, McCall, 1994). The estimated effects are the average for the period of analysis, and because of the short job tenure 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.[39] Subgroup analysis based on workers' characteristics is provided in the next section.

Demographic Subroup 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 different characteristics. Our method for estimating subgroup impacts involves estimating a separate PSM for each subgroup category in each of the sixty months, using these to create matched-pair comparison groups for each subgroup category, and then estimating the effects of job referrals by difference-in-differences for each subgroup category.[40]

38. 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 wages 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/wage.

39. Table D1 in online appendix D provides separate estimates for the 2012 cohort as this cohort has a longer time span for the outcomes to materialize and thus mitigates for censored data, mainly for the time until employment and mean tenure outcomes. The results for the 2012 cohort are qualitatively similar and suggest a better performance for SINE referrals since the time until employment is further reduced and the negative impact on the average mean tenure is smaller.

40. The effects across groups are not directly compared with the overall effects as the difference-in-differences estimations and PSMs are conducted separately for each subgroup (for example, 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 available on 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 who belongs to another subgroup.

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, they show a higher percentage of employment within three months of the 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 positive effects of SINE referrals on the time to find a job are smallest for the youngest workers (eighteen to twenty-four years of age). Indeed, the youngest group has a significantly smaller positive effect than all age groups.[41] The effect on shortening the time until reemployment is significantly greater for the oldest group (fifty-five to sixty-four years) and significantly smaller for the youngest group (eighteen to twenty-four); the estimated effects for the other age groups fall about in the middle of that range.[42] The effects on decreasing tenure in the new job grow steadily larger with age. These effects are significantly different among the five age groups, rising steadily from 2.096 fewer months in the youngest age group (eighteen to twenty-four) to 6.950 fewer months in the oldest age group (fifty-five to sixty-four years). Job referrals reduced reemployment wages the most for the younger prime-age workers (twenty-five to thirty-four), at a rate of 5.9 percent. This reduction is significantly larger than for the youngest workers (eighteen to twenty-four), 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 (thirty-five to forty-four) to 5.2 percent (forty-five to fifty-four), to 5.0 percent (fifty-five to sixty-four).

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

41. The results for the fifty-five to sixty-four age group are influenced by retirement, as Brazil's average retirement age is fifty-six years for men and fifty-three years for women. Prior to 2019, 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).

42. Alternative results provided for the 2012 cohort suggest a clearer stronger effect on shortening the time until reemployment as age increases.

TABLE 6. Estimates of SINE Job Interview Referral Impacts, by Subgroup

Sample subgroup	*Employment within three months*	*Time until employment (months)*	*Mean tenure (months)*	*Reemployment wage (log)*
Age 18–24 years	0.226***	−2.330***	−2.096***	−0.041***
	(0.012)	(0.103)	(0.116)	(0.003)
N	3,928,116	1,761,790	2,657,300	2,649,949
Age 25–34 years	0.267***	−3.107***	−2.762***	−0.059***
	(0.008)	(0.108)	(0.240)	(0.006)
N	8,366,676	4,570,504	5,728,910	5,713,302
Age 35–44 years	0.265***	−3.185***	−3.398***	−0.056***
	(0.009)	(0.127)	(0.449)	(0.008)
N	4,808,100	2,431,800	3,041,026	3,032,629
Age 45–54 years	0.254***	−3.105***	−4.919***	−0.052***
	(0.009)	(0.152)	(0.584)	(0.009)
N	2,416,680	1,130,826	1,401,982	1,398,012
Age 55–64 years	0.242***	−3.884***	−6.950***	−0.050***
	(0.010)	(0.185)	(0.488)	(0.010)
N	779,760	337,192	391,184	390,046
Male	0.275***	−3.180***	−4.028***	−0.064***
	(0.009)	(0.094)	(0.365)	(0.009)
N	11,707,680	6,339,806	7,858,306	7,837,233
Female	0.238***	−3.836***	−4.213***	−0.065***
	(0.009)	(0.124)	(0.303)	(0.005)
N	8,678,488	3,684,396	5,363,858	5,348,523
White	0.260***	−3.750***	−4.503***	−0.078***
	(0.011)	(0.138)	(0.366)	(0.008)
N	9,585,256	4,642,246	6,250,658	6,232,846
Nonwhite	0.259***	−3.207***	−3.696***	−0.052***
	(0.007)	(0.099)	(0.287)	(0.006)
N	10,800,780	5,392,306	6,968,744	6,950,172
Unskilled	0.287***	−3.686***	−4.237***	−0.019**
	(0.010)	(0.184)	(0.485)	(0.008)
N	3,368,556	1,679,206	2,144,906	3,368,556
Semiskilled	0.254***	−3.400***	−3.952***	−0.061***
	(0.009)	(0.100)	(0.318)	(0.006)
N	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)
N	815,440	398,982	503,476	502,265

Source: Authors' calculations.

$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

Note: The table shows the difference-in-differences estimates of the effect of SINE job referrals on labor market outcomes for demographic subgroups. Standard errors clustered at the state level are in parentheses.

larger, at 27 percentage points, versus 24 percentage points for women. On the other hand, a SINE referral reduces women's time until employment by 3.8 months, as opposed to 3.1 months for men. There were less appreciable differences between the genders in the reduction in reemployment job tenure or the reduction in reemployment earnings.

With respect to 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 and the time to reemployment was slightly more reduced 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 according to subjective criteria. This can be particularly problematic in a country as diverse as Brazil. Paixão and others (2012) and Câmara (2015) present results showing discrepancies in data on race between the RAIS database, the IBGE National Household Sample Survey (PNAD), and the national census. The differences are significant, as RAIS presents a higher proportion of whites than PNAD and the census.[43] Using RAIS data, Cornwell, Rivera, and Schmutte (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.

Only 10 percent of workers who seek SINE job search assistance have any tertiary 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: unskilled (from illiterate to completed primary school); semiskilled (partial or completed high school); and skilled (any tertiary education). Most job referrals (63 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 in relative terms, SINE job referrals benefit less skilled job seekers the most. As for the other subgroup regressions, all education

43. Paixão and others (2012) show that in 2009, RAIS identified 61.2 percent of individuals as white, while PNAD identified 54.7 percent of workers as white. Câmara (2015) shows that in 2010, RAIS identified 60 percent of workers as white, whereas the 2010 census identified only 53 percent of workers as white. Race in the RAIS data is disaggregated into five categories (indigenous, white, dark, yellow, brown). For table 6, we divide the data into white and nonwhite.

categories see a big reduction in the time until reemployment as a result of a SINE job referral. The unskilled and semiskilled had the smallest reductions in reemployment job tenure, significantly smaller than for skilled job seekers. 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 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 that SINE job referrals are particularly valuable for the unskilled, especially regarding the probability of finding a job and the reemployment wage.

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, Corbi, and Narita (2018), van Doornik, Schoenherr, and Skrastins (2018), and Cravo and others (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.

The long-term unemployed form an especially vulnerable group of applicants, defined as people who have been unemployed for more than twelve months. Results for this group go in the same direction as results for the full sample, but show differences in the magnitude of the effects (see table 7). 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.

The results for the analysis based on unemployment status show heterogeneity in the impact of the labor intermediation process. In particular, unemployment insurance 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.

TABLE 7. Effects of SINE Job Interview Referrals by UI Receipt and Unemployment Duration

Sample subgroup	*Employment within three months*	*Time until employment (months)*	*Mean tenure (months)*	*Reemployment wage (log)*
UI beneficiaries	0.207***	−2.533***	−2.795***	−0.029***
	(0.008)	(0.103)	(0.486)	(0.005)
N	2,157,364	1,123,086	1,666,510	1,663,046
Non-UI beneficiaries	0.227***	−3.131***	−2.754***	−0.055***
	(0.011)	(0.087)	(0.144)	(0.005)
N	11,483,120	5,808,344	7,532,858	7,510,053
Long-term unemployed	0.298***	−2.122***	−4.974***	−0.099***
	(0.009)	(0.094)	(0.503)	(0.011)
N	7,125,368	2,329,738	4,555,288	4,544,947

Source: Authors' calculations.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: The table shows the difference-in-differences estimates of the effect of SINE job referrals on labor market outcomes for subgroups of workers with different unemployment insurance (UI) status and experiencing long-term unemployment. Standard errors clustered at the state level are in parentheses.

Staff-Assisted versus Self-Service Job Referrals

Technology is changing the way in which public services are provided. Digital channels for labor intermediation have been adopted in many countries; these contribute to the effectiveness and efficiency of the public employment service. Nevertheless, little empirical evidence is available on how mobile technologies affect labor intermediation services and employment outcomes. Dammert, Galdo, and Galdo (2015) provide one exception, as they 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.

To contribute to knowledge on digital channels for labor intermediation, we investigate 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 the placements. This is an important aspect of intermediation services in many developed and developing economies, which have invested in developing online intermediation platforms as a means to increase coverage and reduce costs.

Table 8 shows the effect of SINE online referrals for one group versus the effect of using face-to-face referrals for a control group. The results 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

TABLE 8. Effects of SINE Internet Referrals

Variable	*Employment within three months*	*Time until employment (months)*	*Mean tenure (months)*	*Reemployment wage (log)*
Effect from SINE (relative to control)	0.004	0.569***	0.540**	0.012**
	(0.010)	(0.135)	(0.248)	(0.005)
No. observations	283,872	185,924	198,560	198,079

Source: Authors' calculations.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.
Note: The table shows the difference-in-differences estimates of the effect of SINE job referral on labor market outcomes. The control group received face-to-face job interview referrals. Standard errors clustered at the state level are in parentheses. Results presented in this table should be interpreted with caution because of a shorter time span, as internet-based referrals only started in 2014.

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 for obtaining employment faster, but job matching seems to be more efficient through online services as reemployment wages are higher and job tenure is longer.

Conclusion

This paper relies on the rich administrative records of SINE and RAIS to provide the first impact evaluation of SINE job interview referrals in Brazil on four labor market outcomes: the likelihood of reemployment, time to reemployment, job tenure in the new job, and the monthly reemployment wage rate. Using data from January 2012 to December 2016, we construct propensity scores matched pairs and compute difference-in-differences regressions to measure the impact of SINE 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 wage 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 the system’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 for web-based job interview referrals 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.

Note

We thank Eduardo Pontual Ribeiro, Daniel da Mata, Caio Piza, Rodrigo Quintana, Carlos Corseuil, Miguel Foguel, Paulo Jacinto, Aguinaldo Maciente, Hudson Torrent, Gustavo Alves Tillmann, Sinara Neves, Suely Barrozo Lopes, Ken Kline, Bassam Júnior, Mario Magalhães, Jociany Luz, Karla Carolina Calembo Marra, Wagner Rios, Mariana Almeida, José Ferreiro Espasandin, Diego Fernandes, and Viviane Cesario for their comments on earlier drafts.

References

Aedo, Cristian, and Ian Walker. 2012. *Skills for the 21st Century in Latin America and the Caribbean*. Washington, DC: World Bank.

Betcherman, Gordon, Karina Olivas, and Amit Dar. 2004. "Impacts of Active Labor Market Programs: New Evidence from Evaluations with Particular Attention to Developing and Transition Countries." Social Protection Discussion Paper 0402. Washington, DC: World Bank.

Blundell, Richard, Monica Costa Dias, Costas Meghir, and John Van Reenen. 2004. "Evaluating the Employment Impact of a Mandatory Job Search Program." *Journal of the European Economic Association* 2 (4): 569–606.

Borges, Márcio, Vinicius Lobo, and Miguel Foguel. 2017. "Análise da contribuição do programa de intermediação de mão de obra para os gastos com seguro-desemprego e para arrecadação previdenciária no período recente (2015–2016)." Technical Note 34. Brasília: Institute for Applied Economic Research (IPEA).

Caliendo, Marco, and Sabine Kopeinig. 2008. "Some Practical Guidance for the Implementation of Propensity Score Matching." *Journal of Economic Surveys* 22 (1): 31–72.

Câmara, Guilherme. 2015. "A qualidade das informações de cor ou raça na RAIS: Um estudo comparativo com o censo demográfico de 2010." Thesis, Federal University of Rio de Janeiro (UFRJ).

Carvalho, Cristiano C., Raphael Corbi, and Renata Narita. 2018. "Unintended Consequences of Unemployment Insurance: Evidence from Stricter Eligibility Criteria in Brazil." *Economics Letters* 162 (January): 157–61.

Cornwell, Christopher, Jason Rivera, and Ian M. Schmutte. 2017. "Wage Discrimination When Identity Is Subjective: Evidence from Changes in Employer-Reported Race." *Journal of Human Resources* 52 (3): 719–55.

Cravo, Túlio, Christopher O'Leary, Ana Cristina Sierra, and Leandro Veloso. 2020. "Heterogeneous Effects of Brazilian Unemployment Insurance Reforms on Layoffs." *Economics Letters* 197 (December): 1–4.

Crépon, Bruno, Esther Duflo, Marc Gurgand, and others. 2013. "Do Labor Market Policies Have Displacement Effects? Evidence from a Clustered Randomized Experiment." *Quarterly Journal of Economics* 128 (2): 531–80.

Dammert, Ana Cristina, José C. Galdo, and Virgilio Galdo. 2015. "Integrating Mobile Phone Technologies into Labor Market Intermediation: A Multi-Treatment Experimental Design." *IZA Journal of Labor and Development* 4 (1): 1–27.

Dehejia, Rajeev H., and Sadek Wahba. 2002. "Propensity-Score Matching Methods for Nonexperimental Causal Studies." *Review of Economic and Statistics* 84 (1): 151–61.

DIEESE (Departamento Intersindical de Estatística e Estudos Socioeconômicos). 2016. *Rotatividade no mercado de trabalho brasileiro*. São Paulo: DIEESE.

Heinrich, Carolyn, Alessandro Maffioli, and Gonzalo Vázquez. 2010. "A Primer for Applying Propensity Score Matching: Impact Evaluation Guidelines." Technical Note 161. Washington, DC: Inter-American Development Bank.

IPEA (Institute for Applied Economic Research). 2014. "Funcionamento e desenvolvimentos recentes da intermediação de mão de obra." *Boletim mercado de trabalho* 57. Brasília: IPEA.

———. 2020. "Políticas sociais: acompanhamento e análise." In *Trabalho e renda*, chap. 6. Brasília: IPEA.

Jacobson, Louis, and Ian Petta. 2000. "Measuring the Effect of Public Labor Exchange (PLX) Referrals and Placements in Washington and Oregon." OWS Occasional Paper 2000–06. Washington, DC: U.S. Department of Labor, Office of Workforce Security, Employment, and Training Administration.

Johnson, Terry R., Katherine P. Dickinson, and Richard W. West. 1985. "An Evaluation of the Impact of ES Referrals on Applicant Earnings." *Journal of Human Resources* 20 (1): 117–37.

Lechner, Michael. 2002. "Some Practical Issues in the Evaluation of Heterogeneous Labour Market Programmes by Matching Methods." *Journal of the Royal Statistical Society: Series A* 165 (1): 59–82.

Lobo, Vinicius, and Viviani Anze. 2016. "Duas diretrizes para a reestruturação do Sistema Nacional de Emprego." *Boletim mercado de trabalho* 61, October 2016. Brasília: IPEA.

McCall, Brian P. 1994. "The Effect of Job Heterogeneity on Reservation Wages." *International Economic Review* 35 (3): 773–91.

Michaelides, Marios, and Peter R. Mueser. 2018. "Are Reemployment Services Effective? Experimental Evidence from the Great Recession." *Journal of Policy Analysis and Management* 37 (3): 546–70.

OECD (Organization for Economic Cooperation and Development). 2017. "OECD Policy Memo: Pension Reform in Brazil." Paris: OECD General Secretariat, www.oecd.org/brazil/reforming-brazil-pension-system-april-2017-oecd-policy-memo.pdf.

Paixão, Marcelo, Irene Rossetto, Elisa Moncores, and Guilherme Câmara. 2012. "Investigação sobre qualidade da variável cor ou raça na RAIS através de um estudo comparativo com a PNAD do IBGE." Grupo de Trabalho (GT) 30. Paper presented at the 36th Encontro Anual da ANPOCS, Águas de Lindóia, Brazil, October 21–25.

Pignatti, Clemente. 2016. "Do Public Employment Services Improve Employment Outcomes? Evidence from Colombia." Research Department Working Paper 10. Geneva: International Labour Organization.

Ramos, Carlos A. 2002. "Las políticas del mercado de trabajo y su evaluación en Brasil." *Macroeconomía del desarrollo* 16. Santiago: United Nations Economic Commission for Latin America and the Caribbean.

Rubin, Donald B. 2001. “Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation.” *Health Services and Outcomes Research Methodology* 2 (3–4): 169–88.

Sianesi, Barbara. 2004. “An Evaluation of the Swedish System of Active Labor Market Programs in the 1990s.” *Review of Economics and Statistics* 86 (1): 133–55.

Silva, Joana, Rita Almeida, and Victoria Strokova. 2015. *Sustaining Employment and Wage Gains in Brazil: A Skills and Jobs Agenda.* Washington, DC: World Bank.

Tatsiramos, Konstantinos. 2014. “Unemployment Benefits and Job Match Quality.” *IZA World of Labor* 44 (July): 1–10.

Van Doornik, Bernardus, David Schoenherr, and Janis Skrastins. 2018. “Unemployment Insurance, Strategic Unemployment, and Firm-Worker Collusion.” Working Paper 483. Brasília: Central Bank of Brazil.

Vera, Celia P. 2013. “A Quasi-Experimental Evaluation of the Public Employment Service in Peru.” Zirve University.

Woltermann, Silke. 2002. “Job-Search Methods and Labor Market Transitions.” University of Göttingen.